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The impacts of high-speed rail expansion on short-haul air passenger transport – Evidence from German domestic and international traffic

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ABSTRACT

This study presents an empirical assessment of the influence of (high-speed) long-distance train connections on air travel demand. Specifically, we examine the impact of changes in train travel speed on the number of air passengers within Germany and from Germany to major cities in neighboring countries. Our analysis uses a panel dataset of air passenger numbers on non-stop city-pair routes for the years 2002–2019. We also explore the effects of other variables, including average airfares, night train connections, the presence of low-cost carriers, and the market concentration of airlines (Herfindahl-Hirschman Index). The empirical approach is rooted in a structural gravity model, incorporating recent advancements in gravity modeling. Our results show that improved rail travel speed has a significant impact on the number of airline passengers in a given city pair. Specifically, a 1 % increase in train travel speed corresponds to an overall decrease in air passengers of 0.55 %. This effect is more pronounced for domestic routes, with an average decrease of 0.74 %, as well as for shorter distances and business class passengers. For international connections only, however, the effect is insignificant, but the provision of a night train connection has the potential to shift passenger traffic from air services to train services by between 10 % to over 30 %. Our estimated elasticities can be used to calculate the CO_2 emissions reduction potential for different modal shifts.

1. Introduction

In 2019, the transportation sector accounted for one quarter of the European Union's (EU) greenhouse gas emissions. While emissions from other sectors and total greenhouse gas emissions in the EU have decreased in the past decades, transportation emissions have continued to rise (European Environment Agency, 2022). Consequently, the transportation sector specifically faces a significant challenge in meeting national and international climate goals. Various options exist to achieve these goals, revolving around market-based measures and regulatory instruments aimed at accelerating a green transition. Additionally, the aviation industry is exploring new aircraft technologies, such as electric or hydrogen-powered propulsion systems, and the adoption of sustainable aviation fuels (SAF) promises substantially lower lifecycle emissions than traditional fossil jet fuel. Another measure advocated by governments, especially for short-haul routes, is to encourage the use of less emission-intensive modes of transport. Rail transport, in particular, is significantly less carbon-intensive than aviation. In 2017, long-distance rail transport in Germany emitted 46 g of carbon dioxide equivalents (CO_2e) per passenger kilometer, including emissions from infrastructure construction, compared to 218 g of CO_2e for national aviation (UBA, 2021). Governments promote rail travel by establishing new high-speed rail (HSR) connections or improving the existing network in order to induce a shift in demand from air to rail. Investments in the development of HSR connections have been made particularly in Asia and Europe, with China, Spain, Japan, France, and Germany having the longest HSR networks in 2022 (International Union of Railways, 2023). In Germany, selected railroad lines have been upgraded to 200–230 km/h since the 1970's and new lines have been built for 250–300 km/h since the 1990's. Between 2016 and 2030, the German government plans to invest a further 26.7 billion euros in the construction of new railway infrastructure (BMVI, 2016). In order to fully assess the usefulness of such investments, the modal shift from air travel must be estimated and is therefore of particular interest from a policy-making perspective.

From a theoretical point of view, air and train can be considered as substitutes on short- and medium-haul routes and often act in a duopolistic market environment. Rail can serve as an alternative for air travel if it provides the same gross benefit to the consumer, namely transportation from A to B (Adler et al., 2010; Socorro and Viecens, 2013). The extent to

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which air travel is substituted by rail depends on factors such as travel time differences, fares, frequency of services, accessibility of the transport modes and personal transport preferences. Travelers choose the mode of transport that brings them the highest total utility. Empirical results show that the most important decision criterion besides prices is the total travel time between location A and B (Adler et al., 2010). Assuming a monopoly market in which an airline is the only provider serving a given route, it can theoretically be shown that the introduction of an HSR service shifts demand from air to rail if the HSR service is a sufficiently good substitute (D'Alfonso et al., 2015). Empirical studies on this topic confirm that the introduction of new HSR connections has significantly reduced air traffic on many routes (Clewlow et al., 2014; Castillo-Manzano et al., 2015; Yang et al., 2018; Yu et al., 2021).

In this study, we evaluate the impact of long-distance train services on air travel demand in Germany and from Germany to major cities in neighboring countries. In particular, we estimate the effect of a change in travel speed by train on the number of air passengers on domestic and international short-haul routes. Our empirical approach builds on a structural gravity model and incorporates recent advances in the field of gravity modelling. In this way, the paper makes several empirical and methodological contributions: First, the previous literature focuses on different geographical areas but lacks a study of intra-German data, despite the fact that Germany has the third largest HSR network in Europe and the fifth largest worldwide (International Union of Railways, 2023). Only Clewlow et al. (2014) and Albalate et al. (2015) include data from a limited number of German city pairs in their studies, while most of the further research concerns Spain and China. By leveraging more recent data, we are able to incorporate significant recent infrastructure improvements into our estimates. In addition, previous studies often do not use exact train travel time or travel speed measures, but use a dummy variable for HSR service (Jiménez and Betancor, 2012; Wan et al., 2016; Zhang and Zhang, 2016; Chen, 2017; Zhang et al., 2017). In contrast, we incorporate the average rail travel speed at city-pair level, which we calculate based on the minimum required travel time from timetable data and the straight-line distance between origin and destination. This measure of rail travel speed is independent of the actual train path, so both a change in train speed on the track and a change in the length of the train path can affect air passenger demand. In terms of methodology, to the best of our knowledge, structural gravity models with high-dimensional fixed effects and the Poisson pseudo maximum likelihood (PPML) estimator have not yet been applied to the impact of rail on air transport. We demonstrate that our findings differ from those obtained using the traditional gravity model, which appears to overestimate the train effect by approximately 0.3 percentage points. By employing an Instrumental variable (IV) approach as a robustness check, we confirm the consistency of our estimates. The results of our estimations reveal a significant impact of improved rail travel speed on the number of airline passengers in a given city pair. Specifically, a 1 % increase in train travel speed corresponds to a 0.55 % overall decrease in air passengers, and a 0.74 % decrease for domestic routes. For very short distances, the effect on aviation is much more pronounced (decrease of over −2 %).

The remainder of this paper is structured as follows: Section 2 provides literature on previous empirical studies, Section 3 explains the methodological background and the empirical strategy. Section 4 details data sources and gives some descriptive statistics, followed by Section 5 that includes the empirical findings of our study. The paper closes with a discussion and policy implications in Section 6 and a conclusion in Section 7.

2. Literature review

The effects of the introduction and expansion of HSR rail connections on air traffic have been empirically examined in different studies. Regarding the addressed geographical scope, prior analyses concentrate on domestic routes within Western European countries, primarily France and Spain, as well as Far East Asian countries such as Japan, China, and Korea. Most recent studies primarily focus on examining the impacts of introducing HSR services in China, where HSR connections have increased rapidly over the last decade (Zhang and Zhang, 2016; Chen, 2017; Zhang et al., 2017; Wang et al., 2018; Yang et al., 2018; Yu et al., 2021; Yuan et al., 2023; Li et al., 2024).

Zhang and Zhang (2016) and Yang et al. (2018) model the determinants of air passenger traffic between Chinese cities up to the years 2012 and 2013, incorporating the presence of HSR as one of the explanatory variables. Their findings indicate that air passenger demand decreases by 53 % and 40 % due to the presence of HSR. Chen (2017) and Zhang et al. (2017) both conclude from their empirical analysis that domestic passenger demand in China declines by 20 % after the introduction of HSR on certain city pairs. The studies differentiate the analyzed routes based on travel distance, city type (Chen, 2017), and the level of market competition (Zhang et al., 2017). Wang et al. (2018) investigate, both theoretically and empirically, the effect of train travel speed on air passenger numbers. Using a difference-in-differences approach to study the impact of a temporary 20 % reduction in travel speed in China in 2011, the authors show that air travel increases by 16 % to 22 % in response. Yu et al. (2021) analyze the effects of an increase in rail operating speed on air traffic. Their panel data analysis reveals that a 1 % increase in rail speed results in a reduction of air travel demand by about 0.3 %. Finally, Yuan et al. (2023) and Li et al. (2024) apply a difference-in-differences approach to evaluate the effects of HSR connections on the number of passengers and seats offered by airlines for different domestic routes in China. The inclusion of a HSR dummy variable leads to a 32 % reduction in passengers (Yuan et al., 2023) and an 8 % reduction in seats offered (Li et al., 2024).

Empirical studies with a focus on Europe emerged after new dedicated HSR lines were built on the continent between the 1980's and the beginning of the 2000's, particularly in France, Spain, and Germany. Román et al. (2007) conclude, based on a disaggregated demand model, that the demand for train services between Madrid and Sevilla, measured in market shares, would not exceed 35 %. In a comparable study, Pagliara et al. (2012) estimate the potential market share of HSR between Madrid and Barcelona could reach almost 45 %. Jiménez and Betancor (2012) employ various regression models to analyze the impact of the introduction of HSR in Spain on the frequency of air services, passenger numbers, and airline market shares. Their findings suggest that while the overall demand for transportation services increases, the number of flights decreases by 17 %. The empirical findings of Castillo-Manzano et al. (2015) challenge the theory of (perfect) substitutes between plane and train. They discover that only 14 % of the demand for a new HSR connection in Spain comes from air travel and conclude that HSR primarily generates new demand for itself.

Dobruszkes (2011), Clewlow et al. (2014) and Albalate et al. (2015) analyze the impact of HSR across a number of European countries, including Germany. Specifically, Clewlow et al. (2014) examine the impact of HSR between 1995 and 2004 for 90 airport pairs in France, Germany, Italy, Spain, and the United Kingdom (UK). The study concludes that improving rail travel times significantly reduces short-haul air travel, with dedicated HSR connections reducing air travel by 12 %. However, the authors do not differentiate the results by country to explore potential country differences and the effect of different HSR networks and rail supporting policies. In contrast, Albalate et al. (2015) examine the impact of HSR on supply metrics—such as airline frequencies and seats offered—across routes in France, Italy, Germany, and Spain, providing country-specific results. The authors show that in Spain, airlines cut both seats and flight frequencies on routes competing with high-speed trains, while in Germany only seat numbers decreased. In Italy and France, no significant impact on air service supply was observed. The authors also show that seat reductions are greater at hub airports, except in Germany, where hub airports do not show a net decrease—likely because Germany's HSR network is less centralized than in France and Spain. In a descriptive study, Dobruszkes (2011) also highlights that HSR's impact differs in Germany. In five case studies

Table 1
Overview of empirical literature.

Study	Country/ Region	Period	Methodology/Estimator	Dependent variable (Aviation)	Independent variable (Rail)	Results
Jiménez and Betancor (2012)	Spain	1999–2009	2SLS linear regression model (with airport fixed effects)	Number of flights, market share	HSR dummy	17 % reduction in flights
Clewlow et al. (2014)	Europe (DE, ES, FR, IT, UK)	1995–2009	Panel data regression model (OLS and random effects)	Number of air passengers	HSR dummy, rail travel time	HSR dummy: 12 % reduction in air passengers
Albalate et al. (2015)	Europe (DE, ES, FR, IT)	2002–2010	GLS random effects model	Number of seats and flights	HSR dummy	Statistically significant reduction in number of seats
Castillo-Manzano et al. (2015)	Spain	1999–2012	Time series model (Dynamic linear regression model)	Number of air passengers	HSR passengers	14 % reduction in air passengers (substitution effect)
Wan et al. (2016)	China, Japan, South Korea	1994–2012	Diff-in-diff approach	Number of seats	HSR dummy	Short-haul: 83 % reduction in seats
Zhang and Zhang (2016)	China	2000–2012	Gravity model: Linear regression (with city-year fixed effects)	Number of air passengers	HSR dummy	53 % reduction in air passengers
Chen (2017)	China	2001–2014	Panel data regression model (Fixed effects and random effects)	Number of air passengers, seats and flights	HSR dummy	28 % reduction in air passengers, 25 % reduction in flights, 28 % reduction in seats
Zhang et al. (2017)	China	2010–2013	Panel data regression model (Fixed effects and random effects)	Number of air passengers	HSR dummy	27 % to 28 % reduction in air passengers
Yang et al. (2018)	China	2007–2013	Panel data regression model (Fixed effects and random effects)	Number of air passengers	HSR dummy, rail travel time	HSR dummy: 27 % reduction in air passengers
Wang et al. (2018)	China	2010–2013	Diff-in-diff approach	Number of air passengers, airline yield	HSR dummy, rail speed	A 20 % reduction in rail speed increases air passenger numbers by 16 % to 22 %
Yu et al. (2021)	China	2013–2017	Gravity model: Linear regression (no fixed effects)	Number of air passengers	Rail speed	1 % increase in rail speed leads to a 0.312 % decline in air passengers
Yuan et al. (2023)	China	2008–2017	Diff-in-diff approach	Number of air passengers and flights	HSR dummy, rail frequencies	HSR dummy: 32 % reduction in air passengers, 29 % reduction in passenger flights
Li et al. (2024)	China	2009–2019	Diff-in-diff approach	Number of seats	HSR dummy	8 % reduction in seats

Notes: The review includes literature using regression models. It does not include literature using logit/choice models. HSR = High-speed rail, DE = Germany, ES = Spain, FR = France, IT = Italy, UK = United Kingdom, OLS = Ordinary least squares, 2SLS = Two-stage least squares, GLS = Generalized least squares, Diff-in-Diff = Differences-in-differences.

analyzing HSR's effect on airline supply, the German case showed no significant impact. The author attributes this to Germany's rail network, in which trains do not run exclusively on high-speed lines and make multiple stops due to the population and rail network being more decentralized, which leads to longer travel times.

Table 1 summarizes the empirical studies mentioned, highlighting their geographical and methodological focus. Since 2016, all studies have concentrated on Asia, specifically China, with the most recent study on Western Europe dating back to 2015. The studies utilize various techniques to analyze panel data over different periods, commonly employing general panel data regression and differences-in-differences approaches. Notably, two studies use gravity models: Zhang and Zhang (2016) incorporate gravity model-specific fixed effects, while Yu et al. (2021) estimate the model with panel data regression models (Random and Fixed effects estimators). However, there is a gap in the literature: recent empirical studies focusing on European countries are lacking, as well as studies that comprehensively integrate all modern aspects of gravity modeling like a specific set of fixed effects. In addition, most previous studies use an HSR dummy variable as the variable of interest, while few studies use rail travel time (Clewlow et al., 2014; Yang et al., 2018) or rail speed related variables (Wang et al., 2018; Yu et al., 2021).

3. Methodology and empirical model

3.1. Methodology

We investigate the impact of changes in rail travel speed on the number of air passengers between cities within Germany and from Germany to neighboring cities such as Paris, Brussels, Vienna, or Zurich. In our analysis, we build on recent advances and standards in the field of gravity modelling. This includes the integration of so-called multilateral resistances, which are commonly integrated into the empirical gravity model through the inclusion of time-varying country (exporter/importer) fixed effects (Anderson and van Wincoop, 2003; Feenstra, 2004; Olivero and Yotov, 2012; Yotov et al., 2016). Additionally, to control for any unobservable bilateral resistances and to address concerns of endogeneity related to policy variables included in the model, Baier and Bergstrand (2007) proposed using panel data and incorporating time-invariant country-pair fixed effects. Finally, concerning estimation techniques, rather than employing linear estimators like Ordinary least squares (OLS), it is now common practice to use a non-linear estimator, such as the Poisson pseudo maximum likelihood (PPML) estimator (Yotov et al., 2016). The use of PPML instead of OLS is mainly justified by two reasons: Firstly, gravity datasets often exhibit heteroskedasticity, leading to biased coefficient estimates when employing OLS as an estimator (Santos Silva and Tenreyro, 2006, 2011). Secondly, when using PPML, the dependent variable is not log-linearized, allowing for the consideration of zero flows in the estimation process (Correia et al., 2020).

In the field of aviation economics, only few studies have been published so far that consider these recent advances in gravity modeling.[1] Previous studies examining the impact of rail competition on air

[1] Cristea et al. (2015), Piermartini and Rousová (2013), Oesingmann (2022a) and Oesingmann (2022b) are examples of applying recent methods of gravity modeling to analyzing air transport flows.

transport vary in terms of the methodology used. Early studies apply different forms of transportation choice models based on survey results or scenario modeling (Park and Ha, 2006; Steer Davies Gleave, 2006; Román et al., 2007; Pagliara et al., 2012). In more recent studies, linear Fixed effects (FE) regressions, Random effects (RE), or Two-stage least squares (2SLS) estimates are predominantly employed on panel datasets (Jiménez and Betancor, 2012; Clewlow et al., 2014; Castillo-Manzano et al., 2015; Zhang and Zhang, 2016; Chen, 2017; Zhang et al., 2017; Yu et al., 2021). Yang et al. (2018) tackle the issue of heteroskedasticity by conducting a variance component analysis. The number of air passengers (demand) or the number of air seats offered (supply) between two cities serves as the dependent variable in the mentioned studies. To estimate the effects of HSR, most models introduce an HSR dummy variable. However, both Wang et al. (2018) and Yu et al. (2021) use rail travel speed as an indicator of the impact of rail services.

3.2. Empirical strategy

In our initial regression, we leave out any fixed effects to enable the estimation of coefficients for the traditional gravity model control variables. Equation (1) gives the regression equation of a simple gravity model in PPML form. Since we employ this non-linear estimator, the dependent variable is not log-linearized, allowing the regression to include zero values in the dependent variable.

$$X_{ijt} = exp\left[\beta' GRAVITY_{it,jt,ij} + \gamma_1 lnTrainspeed_{ijt}\right] + \varepsilon_{ijt} \tag{1}$$

X_{ijt} denotes the number of air passenger flows from city i to city j at time t ($Airpax_{ijt}$). The vector $GRAVITY_{it,jt,ij}$ consists of a set of time-varying and time-invariant control variables, including the average gross domestic product (GDP) per capita of city i and city j ($GDPc_{it,jt}$), the total population size of both cities ($Pop_{it,jt}$), distance and common language ($Dist_{ij}$, $Lang_{ij}$), and a dummy variable denoting international air passenger flows ($Border_{ij}$). Our variable of interest, $Trainspeed_{ijt}$, represents the travel speed by train measured in km/h between the cities i and j at time t. ε_{ijt} gives the error term, and robust standard errors are clustered by city pair. All independent variables, with the exception of the dummy variables, are converted into their natural logarithmic form.

The variable $Trainspeed_{ijt}$ can be treated as exogenous in our model. In Germany, investment decisions in federal transport infrastructure projects, such as HSR lines, are primarily driven by the benefits and costs assessed through a formal benefit-cost analysis. The majority of the benefits from HSR projects arise from travel time savings for existing rail users, while modal shifts from air to rail contribute only a minor share. For example, in the case of the planned new and upgraded HSR corridor between Bielefeld and Berlin, approximately 55 % of the total benefits are attributed to time savings for current rail passengers, whereas less than 5 % result from shifts in demand from air travel to rail (BMDV, n.d.).

In the next step, we expand our gravity model. As outlined in the introduction, the substitution between plane and train depends not only on the travel time between two cities but also on the prices of the two modes. The variable $Trainfare_t$ is a yearly measure for long-distance train fares, comparable to an economy-wide price index. The variable is derived from yearly average train revenues per passenger kilometer. We also insert the variable $Airfare_{ijt}$ which gives the annual average airfare on an origin–destination (O-D) basis, weighted by passengers, for city pair *ij* in year *t*. Given that the variable on airfares is only available for observations with passenger flows greater than zero, zero-flows will now be dropped from the regression. As introduced by Baier and Bergstrand (2007), we also include time-invariant city-pair fixed effects (ν_{ij}). These fixed effects capture all bilateral, time-invariant controls. Moreover, city-pair fixed effects in panel data settings can help address endogeneity concerns related to specific variables (Baier and Bergstrand, 2007; Yotov et al., 2016).

For a further regression, we additionally include time-varying city i and city j fixed effects (λ_{it}, μ_{jt}). The city-specific fixed effects capture observable and unobservable multilateral resistances (Feenstra, 2004; Olivero and Yotov, 2012; Yotov et al., 2016). These resistances include demand and supply factors such as the accessibility of the origin and destination transport nodes, hub status of the airports, as well as airport user fees and train track access charges. Equation (2) represents the structural version of our gravity model and by this our main model. Since the variable $Trainfare_t$ varies only by year and not across city pairs, it is excluded from the regressions due to collinearity with the time-varying fixed effects, which capture the same variation.

$$X_{ijt} = exp\left[\gamma_1 lnTrainspeed_{ijt} + \gamma_2 lnAirfare_{ijt} + \nu_{ij} + \lambda_{it} + \mu_{jt}\right] + \varepsilon_{ijt} \tag{2}$$

We perform different robustness checks and additional regressions. In a first step, we insert an additional rail-specific dummy variable, $Ntrain_{ijt}$, which takes the value one if a night train connection exists on the respective city pair. We will also include two variables that impact air passenger numbers: a dummy variable, LCC_{ijt}, indicating the presence of a low-cost carrier (LCC), and a variable HHI_{ijt}, giving the degree of market concentration. The market concentration is measured by the Herfindahl-Hirschman Index (HHI) which we calculate based on airline data for each city-pair/year combination. We also run the regressions on two subsets obtained by dividing the original data set into observations with a distance greater/smaller than the median value of the distance variable and by considering only German domestic observations. Lastly, we compare our PPML estimated results that incorporate the airfare variable with different linear estimators, that is standard OLS (Equation (3)) and an IV-approach with 2SLS to address possible residual issues of endogeneity of airfares. Endogeneity, caused by the reverse causality between air passengers and air fares, may lead to biased estimates.[2]

$$lnX_{ijt} = \gamma_1 lnTrainspeed_{ijt} + \gamma_2 lnAirfare_{ijt} + \nu_{ij} + \lambda_{it} + \mu_{jt} + \varepsilon_{ijt} \tag{3}$$

The two stages of the 2SLS approach are shown in equations (4a) and (4b), with the instrument variable IV_{ijt}. We use airfares in other markets (routes) with a similar length of haul and the HHI index as instrument variables. Both instruments are commonly used in IV approaches involving airfares to estimate price elasticities and address endogeneity concerns. While the variable airfare in other markets (routes) refers to a Hausman-type price instrument, the HHI index refers to the instrument type of competition and market power (Mumbower et al., 2014; Morlotti et al., 2017).

$$lnAirfare_{ijt} = \pi_1 lnIV_{ijt} + \pi_2 lnTrainspeed_{ijt} + \nu_{ij} + \lambda_{it} + \mu_{jt} + \eta_{ijt} \tag{4a}$$

$$lnX_{ijt} = \gamma_1 lnTrainspeed_{ijt} + \gamma_2 \widehat{lnAirfare}_{ijt} + \nu_{ij} + \lambda_{it} + \mu_{jt} + \varepsilon_{ijt} \tag{4b}$$

4. Data and data sources

4.1. Data sources

The dataset is mainly based on two data sources: The air transport-related Sabre Market Intelligence (MI) database (Sabre, 2023) and the train schedule database Fernbahn.de (Grahnert and Krings, 2023). The Sabre MI database is a subscription-based product of the company Sabre Inc. which is a global distribution system provider for air tickets. This database includes monthly data on O-D passenger flows between individual airports and shows characteristics such as the number of air passengers, the average fare paid and the operating airline. Fernbahn.de is a freely accessible database that includes all long-distance timetables of Deutsche Bahn (German Railways) between 1987 and 2023. Since the

[2] Please note that apart from the airfare variable, the low-cost carrier variable may exhibit potential endogeneity. Therefore, we use this variable not in the main but only in additional regressions.

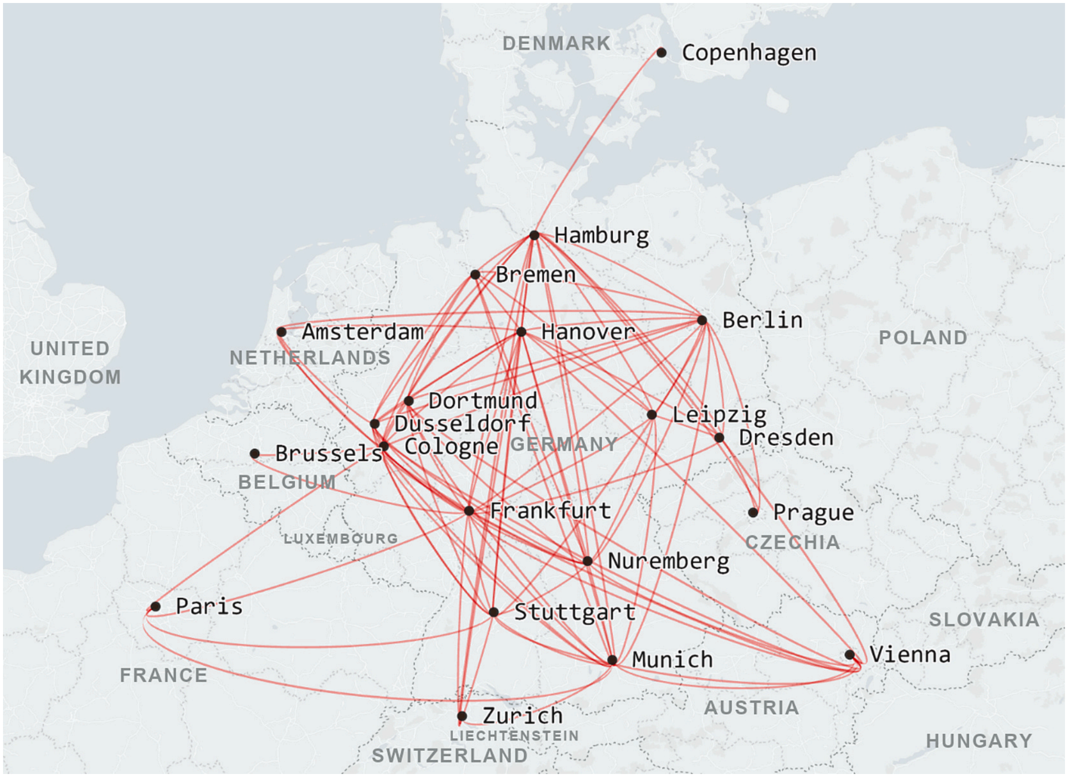

Fig. 1. Domestic and international city-pair connections.
Source: Own figure.

data in the Sabre MI database is available back to the year 2002, and we aim to exclude the effects of the COVID-19 pandemic, our dataset is limited to the years 2002 to 2019.

Our analysis focuses on direct (non-stop) passenger flows and non-transfer rail connections, as only these offer competitive travel times in the considered (ultra)-short-haul markets. Hence, data limitations on rail timetable database would restrict the ability to include rail transfer connections, but those passengers using two long-distance trains account for only around 14.5 % of the total rail passengers (Brand and Sieg, 2020). During the observation period, direct rail services operated regularly only between major German cities. Additionally, city pairs without direct train connections several times a day were excluded from the dataset for the reason of connectivity. We therefore consider connections to and from cities in Germany with an own airport and more than 500,000 inhabitants in 2019 (Berlin, Bremen, Cologne, Dortmund, Düsseldorf, Dresden, Frankfurt, Hamburg, Hanover, Leipzig, Munich, Nuremberg, Stuttgart). In the neighboring countries of Germany, we each consider the most populous city as the origin or destination of a cross-border connection (Amsterdam, Brussels, Copenhagen, Paris, Prague, Vienna, Zurich). In almost all cases, this city is also the capital city, with the exception of Zurich in Switzerland. As the database Fernbahn.de is restricted to city pairs with origin and/or destination in Germany, our analysis is focused on German domestic and cross-border connections.[3] Fig. 1 shows the resulting 94 intra-German and cross-border city-pair connections and the corresponding geographical locations of the origin and destination cities in the dataset.

The Sabre MI database provides information on the number of air passengers ($Airpax_{ijt}$), average airfare ($Airfare_{ijt}$), presence of LCCs (LCC_{ijt}), and airline market concentration (HHI_{ijt}). LCCs are defined as those listed in the Low-Cost Monitor of the German Aerospace Center (DLR) (Berster et al., 2019). Market concentration is calculated as the square sum of the market shares of the individual airlines in a city-pair market, whereby airlines owned by the same company are treated as a single airline (e.g. Lufthansa and Lufthansa City Line as part of the Lufthansa Group). From the Deutsche Bahn timetables obtained from Fernbahn.de, we extract the train connection with the minimum possible travel time for each timetable year and city pair. The focus on the fastest connections is justified by the fact that it can be assumed that most passengers book the fastest trains. Slower trains often serve multiple intermediate stops or have different starting or ending points, making

Table 2
Variables and data sources.

Variable	Description	Unit	Data source(s)
$Airpax_{ijt}$	Number of O-D air passengers	–	Sabre MI Database
$Trainspeed_{ijt}$	Train travel speed (average)	km/h	Fernbahn.de
$Airfare_{ijt}$	Airfare (average)	€2019	Sabre MI Database
$Dist_{ij}$	Distance	km	Sabre MI Database
$GDPc_{it,jt}$	GDP per capita	€2019	Eurostat, City of Zurich
$Pop_{it,jt}$	Population	–	Eurostat, City of Zurich
$Border_{ij}$	International connection	Dummy	–
$Lang_{ij}$	Same official language	Dummy	CEPII Gravity Database
$Ntrain_{ijt}$	Night train	Dummy	Fernbahn.de
$Trainfare_{t}$	Train fare per pkm (average)	€2019	German Railways (DB), Federal Network Agency
LCC_{ijt}	Low-cost carrier	Dummy	Sabre MI Database
HHI_{ijt}	Herfindahl-Hirschman Index in air travel market	between 0 and 1	Sabre MI Database

Notes: O-D = Origin and destination, pkm = passenger kilometer.

[3] Train schedule data that comprehensively covers multiple European countries, such as the MERITS database provided by the International Union of Railways (UIC), is not freely accessible but comes with additional costs and is intended for railway companies. https://uic.org/passenger/passenger-services-group/merits.

Table 3
Summary statistics.

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
$Airpax_{ijt}$	3,342	98,711	165,882	0	904,661
$Trainspeed_{ijt}$	3,342	95.83	21.61	35.95	169.80
$Airfare_{ijt}$	2,877	123.88	75.19	10.26	2,287.88
$Dist_{ij}$	3,342	344.08	170.32	34.43	768.31
$OrgGDPc_{it}$	3,342	64,764	26,006	28,647	168,628
$DesGDPc_{jt}$	3,342	64,770	26,000	28,647	168,628
$OrgPop_{it}$	3,342	1,135,666	787,400	364,528	3,658,229
$DesPop_{jt}$	3,342	1,135,666	787,099	364,528	3,658,229
$Border_{ij}$	3,342	0.30	0.46	0	1
$Lang_{ij}$	3,342	0.16	0.37	0	1
$Ntrain_{ijt}$	3,342	0.09	0.28	0	1
$Trainfare_{t}$	3,342	0.14	0.01	0.13	0.15
LCC_{ijt}	3,342	0.46	0.50	0	1
HHI_{ijt}	2,877	0.79	0.23	0.23	1

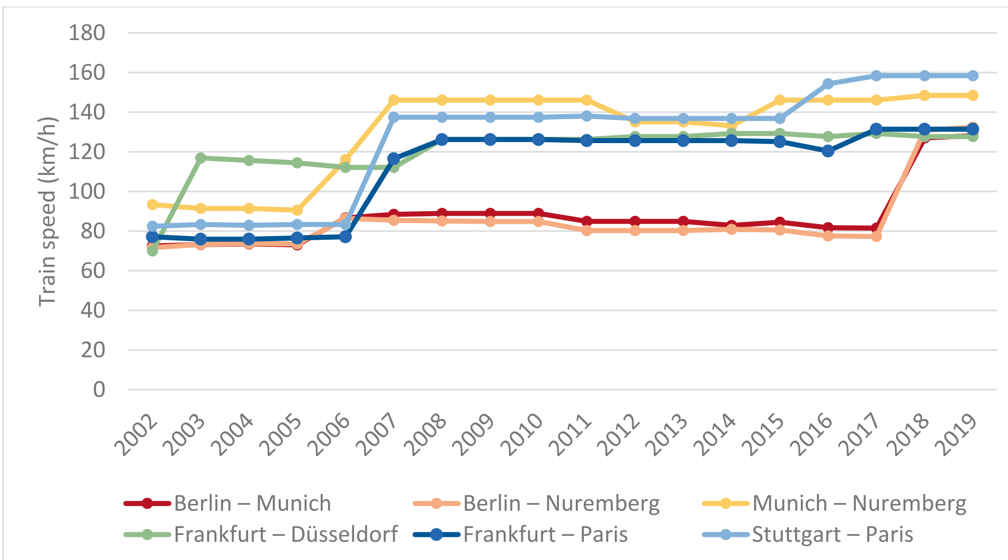

Fig. 2. Development of train travel speed on selected routes between 2002 and 2019.
Source: Own figure.

them more relevant for passengers with other origins or destinations. Based on the minimum travel times, we calculate the average rail travel speed ($Trainspeed_{ijt}$) based on the straight-line distance between the origin and destination city center. This measure of rail travel speed is independent of the actual train path, so that both a change in train speed on the track as well as a change in the length of the train path can have an effect on air passenger demand. As the variable enters our model in logarithmic form, it can be interpreted as an effect of a percentage change in speed. Consequently, the result also applies to the actual speed of the train on the track as long as the length of the train path remains unchanged. For rail, there is no average price data at the city-pair level available. However, in order to account for changes in the national price level in rail transport relative to air transport, we construct the variable $Trainfare_{t}$, which represents the average annual price paid per passenger kilometer in long-distance rail transport. Data sources for this variable are annual reports of Deutsche Bahn and publications of the German Federal Network Agency. City GDP per capita and population data are from Eurostat and the City of Zurich. The dummy variable same official language ($Lang_{ij}$) comes from the CEPII Gravity Database (Conte et al., 2022). Table 2 summarizes all the variables and their data sources.

4.2. Summary and descriptive statistics

The resulting dataset includes 188 O-D city pairs (counted in both directions) that had regular direct connections during the observation period between 2002 and 2019. This results in a total of 3,342 observations. Summary statistics of the variables are shown in Table 3.[4] The average number of air passengers per city pair and year is around 99,000. The maximum of about 905,000 passengers was observed on the Cologne-Berlin route in 2011. The average rail travel speed in relation to the straight-line distance is 96 km/h. The fastest average speed of just under 170 km/h was achieved without intermediate stops between 2005 and 2007 on the Hamburg-Berlin route. The distance between the origin

[4] We tested the data set for heteroscedasticity using the White test, and as is common with gravity data, our data set also violates the assumption of homoscedasticity. As explained in the Methodology section, this favors using a non-linear estimator like PPML.

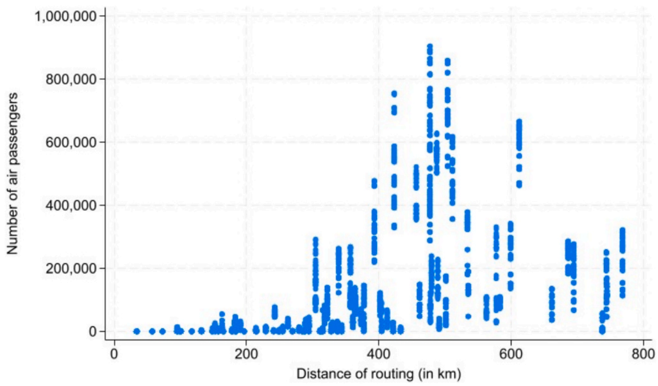

Fig. 3. Distance of routing and air passenger numbers.
Source: Own figure. Notes: The figure plots each observation (origin-destination-year combination) in the dataset according to the routing distance (in km) and the number of air passengers for the period from 2002 to 2019.

and destination city ranges from 34 km (Düsseldorf – Cologne) to 768 km (Düsseldorf – Vienna).[5]

Fig. 2 illustrates the development of train travel speed on the city pair routes that experienced the highest percentage increases between 2002 and 2019. The relative speed increase on these routes ranges from 59 % to 92 %. HSR lines with maximum permissible speeds of at least 300 km/h were introduced on all these routes during the period under consideration. These HSR lines include: Cologne – Frankfurt (opened August 2002), Nuremberg – Ingolstadt (May 2006), the LGV Est between Paris and Strasbourg (first section in June 2007, second section in July 2016), Erfurt – Leipzig (December 2015) and Ebensfeld – Erfurt (December 2017).

Fig. 3 plots the relationship between city-pair distance and number of air passengers. For distances of less than 300 km, there is only little air passenger traffic, with car and rail presumably dominating this segment. The highest air passenger numbers can be observed between 300 km and 650 km, in particular on domestic routes. The advantages of air travel increase with distance and, in combination with stronger demand on domestic routes, lead to high traffic volumes. City-pair connections with a distance between 650 km and 800 km are exclusively international connections, which in turn have lower passenger numbers.

5. Results and discussion

5.1. Results of main specifications

Table 4 shows the results for the different specifications of our main empirical model. Regressions are estimated with the Stata command ppmlhdfe by Correia et al. (2020). Columns 1 and 2 report the traditional versions of the gravity model, while columns 3 to 6 report the structural versions as fixed effects are included. As can be seen, almost all parameter estimates are significantly different from zero. In column 1 and 2, the parameter estimates for the traditional gravity variables, distance, GDP per capita, population, language, and border, have all the expected signs.[6] Distance has a strongly positive effect on the number of air passengers because with increasing distance the higher travel speed of the aircraft compensates for the longer access and egress times compared to rail. This substitution effect is larger in the short-haul markets considered than the generally negative effect of distance on total transport demand, resulting in a positive net effect. In the structural versions of the gravity model, city-pair and city-year fixed effects control for heterogeneity between city pairs and over time. The main variable of interest, train speed, has a significant negative effect on the number of air passengers in all six specifications. In our preferred structural version of the gravity model (column 5) the coefficient is −0.55, implying that a 1 % increase in train travel speed decreases the number of air passengers by −0.55 %. The parameter −0.55 can be used to estimate the expected decrease in air passenger numbers due to the development of HSR. For example, increasing rail speed by 20 % from an average of 150 km/h to 180 km/h would lead to an 11 % decrease in air passengers on a specific route.

The airfare variable is highly significant and its parameter value of about −0.37 can be interpreted as a price elasticity of demand, meaning that a 1 % increase in the airfare results in a decrease of the number of air passengers of −0.37 %. For comparison, there are only a few other studies estimating price elasticities for European air transport markets with distances of less than 800 km, and some of these studies are quite dated. Jorge-Calderón (1997) uses data on international European routes from 1989 and finds an average price elasticity of −0.71 for markets with distances of up to 600 km. Morlotti et al. (2017) analyse price elasticities on EasyJet routes from Amsterdam in 2015 and estimate them to be −0.57 for the Amsterdam – Berlin route (578 km) and −0.54 for the Amsterdam – Hamburg route (367 km). Compared to these findings, our result appears to be broadly in line with the literature, though slightly below previous estimates. We analyse remaining possible endogeneity despite the use of panel data and city pair effects in the robustness section using an IV-approach (refer to section 5.3).

In specification 3, without city-year fixed effects, the parameter estimate of train fare is significantly positive and above one, which can be interpreted as a cross-price elasticity of about 1.3, meaning that a 1 % increase in the price level of long-distance train services increases air travel demand by 1.3 %. When we also include the airfare variable, the cross-price elasticity reduces to about 0.6 %. In our preferred specifications (columns 5 and 6) we cannot include the train fare variable, as it would be completely absorbed by the city-year fixed effects.

5.2. Robustness checks with different variables and scopes

To validate the robustness of our results, alternative specifications of our preferred model specification are tested. The results are presented in Table 5. Column 1 reports the results of our preferred specification for comparison. Column 2 additionally includes the night train dummy and column 3 the LCC dummy and the HHI variable. Column 4 includes the airfare variable instead of the LCC dummy and HHI variable. The parameter estimates for the additional variables are all significant and have the expected signs: Night train connections and greater market concentration among airlines reduce air passenger volumes by 10 % and 30 % respectively (see column 3), whereas the market entry of LCCs increases air passenger demand by almost 20 %. The parameter estimate for the variable of our main interest, train speed, differs only marginally between specifications. The same applies to the parameter of airfare, which together supports the robustness of our results.

Finally, we explore how the results differ for subsamples of our dataset and split the dataset in a first step to longer and shorter distances at the median city-pair distance (344 km). In the subsample with observations equal to and less than 344 km distance, the share of domestic routes is 80 %, and in the subsample with observations greater than 344 km distance, the share of domestic routes is 60 %. As can be seen in Table 6, the effect of a relative increase in rail travel speed is considerably larger for city-pair markets with shorter distances (<344 km). This seems to confirm the observation that especially on shorter routes, the upgrading of the rail network to higher speeds has drastically

[5] Airfare data, used to construct the HHI variable, is only available for observations with a passenger count above zero. As our dataset also includes instances where the passenger count for a given O-D city pair in a given year is zero, the number of observations with passenger data exceeds those with airfare and HHI data.

[6] We tested for multicollinearity and the mean VIF (variance inflation factor) of all variables in the model is 1.54. The variables border and language have the largest VIF with a value of 2.34 and 2.03. The other variables show values between 1 and 2.

Table 4
Main Gravity model specifications.

	(1)	(2)	(3)	(4)	(5)	(6)
	Airpax	*Airpax*	*Airpax*	*Airpax*	*Airpax*	*Airpax*
lnDist	2.170***	2.159***				
	(0.188)	(0.188)				
lnGDPc	1.473***	1.496***	0.394	0.669**		
	(0.202)	(0.202)	(0.317)	(0.271)		
lnPop	1.035***	1.052***	0.490	−0.061		
	(0.112)	(0.112)	(0.508)	(0.450)		
Lang	0.646***	0.655***				
	(0.205)	(0.206)				
Border	−2.174***	−2.189***				
	(0.198)	(0.199)				
lnTrainspeed	−0.857***	−0.895***	−0.602***	−0.768***	−0.546***	−0.595***
	(0.311)	(0.317)	(0.182)	(0.180)	(0.146)	(0.128)
lnTrainfare		1.908***	1.269***	0.595***		
		(0.126)	(0.121)	(0.104)		
lnAirfare				−0.332***		−0.368***
				(0.029)		(0.029)
City-pair FE	No	No	Yes	Yes	Yes	Yes
City-year FE	No	No	No	No	Yes	Yes
N	3,342	3,342	3,342	2,876	3,304	2,836
pseudo R2	0.790	0.795	0.967	0.969	0.983	0.984

Notes: All models are estimated with PPML. (Robust) standard errors, clustered by city pair, are given in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. FE = fixed effects; city-year FE include both origin and destination city-year FE.

Table 5
Main model specification with additional variables.

	(1)	(2)	(3)	(4)
	Airpax	*Airpax*	*Airpax*	*Airpax*
lnTrainspeed	−0.546***	−0.582***	−0.536***	−0.639***
	(0.146)	(0.148)	(0.134)	(0.129)
Ntrain		−0.077***	−0.104***	−0.089***
		(0.024)	(0.024)	(0.022)
LCC			0.196***	
			(0.030)	
HHI			−0.298***	
			(0.048)	
lnAirfare				−0.374***
				(0.029)
City-pair FE	Yes	Yes	Yes	Yes
City-year FE	Yes	Yes	Yes	Yes
N	3,304	3,304	2,836	2,836
pseudo R2	0.983	0.983	0.985	0.985

Notes: All models are estimated with PPML. (Robust) standard errors, clustered by city pair, are given in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. FE = fixed effects; city-year FE include both origin and destination city-year FE. To calculate (semi-) elasticities of the dummy variables: 100*(exp(β) –1).

reduced or completely eliminated air traffic. In addition, the price elasticity is found to be lower in absolute terms on shorter distances. This seems plausible, as an even higher proportion of business travellers and time-sensitive leisure travellers can be assumed on these routes.

To approve the assumption that business related travellers are more time sensitive and travel on shorter routes, we retrieved additional data categorised by booking class. Note that, due to data availability, this is only possible for the period 2011–2019. Furthermore, the purchased booking class does not indicate the purpose of travel, but rather the booked cabin type. The regressions confirm that an increase in train speed has a much greater impact on business class passengers than on those who booked standard economy tickets. The regression coefficient for the train speed variable is −2.75 (Table 7) which is close to the impact reported for shorter distances in column 1 of Table 6 of −2.47. Moreover, when plotting route distances against the share of business class passengers, the fitted line slopes downward, indicating that the proportion of business class passengers decreases as route length increases (Fig. 4).

In an additional analysis, we separate our dataset to domestic observations only and city pairs with destinations in neighboring countries (see Table 8). Compared to the specifications of our model shown in

Table 6
Regressions differentiated by city-pair distance.

	(1)	(2)	(3)	(4)	(5)	(6)
	Airpax	*Airpax*	*Airpax*	*Airpax*	*Airpax*	*Airpax*
lnTrainspeed	−2.473***	−1.664***	−2.078***	−0.435***	−0.434***	−0.500***
	(0.556)	(0.413)	(0.476)	(0.159)	(0.146)	(0.147)
Ntrain		0.000	0.000		−0.095***	−0.087***
		(.)	(.)		(0.026)	(0.026)
LCC		0.163***			0.173***	
		(0.052)			(0.040)	
HHI		−0.874***			−0.266***	
		(0.138)			(0.054)	
lnAirfare			−0.284***			−0.394***
			(0.069)			(0.034)
Scope	<344 km	<344 km	<344 km	>344 km	>344 km	>344 km
City-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
City-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,837	1,367	1,367	1,368	1,339	1,339
pseudo R2	0.983	0.986	0.984	0.977	0.981	0.981

Notes: All models are estimated with PPML. (Robust) standard errors, clustered by city pair, are given in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. FE = fixed effects; city-year FE include both origin and destination city-year FE. To calculate (semi-) elasticities of the dummy variables: 100*(exp(β) –1).

Table 7
Regressions differentiated by flight booking class.

	(1)*Airpax*	(2)*Airpax*	(3)*Airpax*
	Total air passengers	Economy class passengers	Business class passengers
lnTrainspeed	−0.431***	−0.411***	−2.753***
	(0.116)	(0.111)	(0.495)
City-pair FE	Yes	Yes	Yes
City-year FE	Yes	Yes	Yes
Time period	2011–2019	2011–2019	2011–2019
N	1,638	1,638	1,633
pseudo R2	0.995	0.995	0.953

Notes: For the purposes of this analysis, passengers with premium, business or first-class tickets are categorized as business class passengers. All regressions include both domestic and international observations, and are estimated with PPML. (Robust) standard errors, clustered by city pair, are given in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. FE = fixed effects; city-year FE include both origin and destination city-year FE.

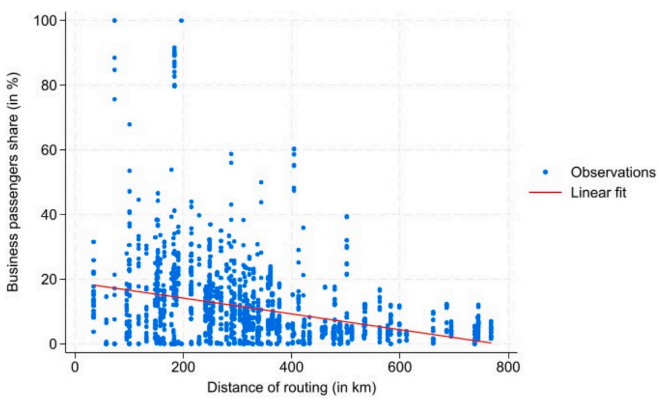

Fig. 4. Distance of routing and business passengers share.
Source: Own figure. Notes: This figure plots each observation (origin-destination-year combination) in the dataset according to routing distance (in km) and business passengers share (in %) for the period from 2011 to 2019.

Table 5, the effect of an increase in rail speed on air passenger numbers rises to almost −0.8 % for domestic observations, while the price elasticity remains similar at around −0.3 %. The results are consistent with the regressions shown in Table 6, where the impact of higher rail speed is much larger for shorter distances below 344 km, consisting of 80 % domestic routes in the subsample, than for longer distances, consisting of only 60 % domestic routes. For international connections, the effect is insignificant, indicating that faster train speeds do not encourage travelers to switch from air to rail for cross-border trips. In contrast, the effect is more pronounced for cross-border night train connections (−36 %) compared to both the full sample and the domestic-only sample. However, it should be noted that the number of observations in the cross-border sample is substantially smaller than in the main or domestic-only regressions.

5.3. Robustness checks with different estimators

Table 9 presents additional regressions using OLS and 2SLS, compared to the PPML estimator. For the OLS and 2SLS regressions, we employ the Stata commands reghdfe and ivreghdfe by Correia (2023) which facilitate the estimation of these models with multiple levels of fixed effects. The first column presents the PPML regressions, including the variable Airfare without any fixed effects. Airfare is not significantly different from zero in the model specification shown in column 1. This indicates that the airfare variable is endogenous in this specification, because parameter estimates are biased towards zero in the presence of endogeneity and unobserved market characteristics may insufficiently be controlled for. In our preferred model specification (column 2), the structural approach with high-dimensional fixed effects controls for unobservable market characteristics. Columns 3 and 4 present the OLS estimates. The coefficient for the train speed variable is notably larger compared to the PPML regressions. The airfare variable shows a positive effect in the model without fixed effects but becomes insignificant once the full set of fixed effects is included. The last two columns report results from an IV approach. In column 5, the airfare variable is instrumented using airfare in other markets (routes) with a similar length of haul, while in the final column, we include the HHI index as instrument.

Compared to previous studies, the impact of HSR or changes in train speed on passenger numbers appears to be significantly overestimated

Table 8
Regressions for domestic and international observations.

	(1)	(2)	(3)	(4)	(5)	(6)
	Airpax	*Airpax*	*Airpax*	*Airpax*	*Airpax*	*Airpax*
lnTrainspeed	−0.737***	−0.796***	−0.780***	−0.042	0.131	−0.047
	(0.163)	(0.138)	(0.140)	(0.650)	(0.604)	(0.531)
Ntrain		−0.076***	−0.072***		−0.358***	−0.222***
		(0.019)	(0.018)		(0.045)	(0.058)
LCC		0.240***			0.121***	
		(0.035)			(0.041)	
HHI		−0.446***			−0.270***	
		(0.040)			(0.094)	
lnAirfare			−0.315***			−0.340***
			(0.041)			(0.085)
Scope	Domestic	Domestic	Domestic	Cross-border	Cross-border	Cross-border
City-pair FE	Yes	Yes	Yes	Yes	Yes	Yes
City-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,336	1,905	1,905	858	856	856
pseudo R2	0.988	0.991	0.989	0.974	0.978	0.978

Notes: All models are estimated with PPML. (Robust) standard errors, clustered by city pair, are given in parentheses. *p < 0.10; **p < 0.05; ***p < 0.01. FE = fixed effects; city-year FE include both origin and destination city-year FE. To calculate (semi-) elasticities of the dummy variables: 100*(exp(β)–1).

Table 9
Regressions with different estimators.

	(1) PPML	(2) PPML	(3) OLS	(4) OLS	(5) 2SLS	(6) 2SLS
	Airpax	*Airpax*	*lnAirpax*	*lnAirpax*	*lnAirpax*	*lnAirpax*
lnTrainspeed	−0.890***	−0.595***	−2.679***	−1.830***	−1.888***	−2.207***
	(0.316)	(0.128)	(0.557)	(0.680)	(0.674)	(0.723)
lnAirfare	−0.073	−0.368***	0.715***	−0.151	−0.448***	−2.055***
	(0.057)	(0.029)	(0.131)	(0.104)	(0.120)	(0.572)
Instrument variable					Airfares in other markets	HHI index
Controls	Yes	No	Yes	No	No	No
City-pair FE	No	Yes	No	Yes	Yes	Yes
City-year FE	No	Yes	No	Yes	Yes	Yes
N	2,877	2,836	2,877	2,836	2,836	2,836

Notes: (Robust) standard errors, clustered by city pair, are given in parentheses. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$. FE = fixed effects; city-year FE include both origin and destination city-year FE.

when using OLS and 2SLS. In these models, the elasticity estimates, including fixed effects, approach or exceed −2. Regarding the airfare variable, the 2SLS regressions in column 5—where price is instrumented using fare data from other markets—yield price elasticity estimates of approximately −0.45, which differ only slightly from our PPML estimates (−0.37). However, when the HHI index is used as an instrument, the price elasticity increases to −2, which again appears overestimated compared to previous studies (Mumbower et al., 2014; Morlotti et al., 2017). Based on these robustness checks, we consider our PPML estimates with fixed effects to be the preferred specification, although it has to be acknowledged that the price elasticities may be slightly underestimated by around 0.1 percentage points.

6. Discussion and policy implications

Our findings complement earlier research on the European HSR market. Previous studies have estimated reductions in air travel demand of between −12 % and −14 % when analysing the impact of new HSR connections—typically captured using a dummy variable (Clewlow et al., 2014; Castillo-Manzano et al., 2015). These results are not directly comparable to our findings, as our analysis focuses on the effects of travel speed improvements within the (HSR) rail network. Our overall estimates for intra-German and cross border connections indicate elasticities of the train speed variable of −0.55 %. A 20 % increase in average rail speed, from 150 km/h to 180 km/h for example, would then decrease air passengers by 11 %. In a methodology-wise more comparable study on the impact of HSR in China (Yu et al., 2021), the authors find that increasing train travel speed by 1 % results in a 0.3 % decline in air passenger numbers. A 20 % increase in rail speed would then only result in 6 % of passengers switching from air to rail. Our estimates overall indicate higher elasticities, particularly for domestic only and very short distances (−0.7 %; −2.5 %) which suggests that train speed elasticities appear to rise as travel distances decrease.

Variations in the overall length of HSR networks and specific route characteristics across countries therefore can lead to differing outcomes between studies. The average route length in the Chinese HSR network is significantly higher than average routing length in Germany (International Union of Railways, 2023). Our findings suggest that the substitution effect between rail and air travel reduces as travel distances and travel times increase. However, in the case of international connections, the border effect seems to prevent this substitution. Moreover, comparisons of studies involving Germany and other European countries in the literature section show that Germany's decentralized rail network may affect air travel differently than the more centralized networks in Spain and France. Multiple stops lead to an increase in travel time; on the other hand, having multiple economic and airline hub cities prevents the effects from being concentrated to one city. Finally, it is important to note that our estimated values represent annual averages, and elasticities may fluctuate throughout the year. For example, a higher share of leisure travelers in the summer compared to winter may affect elasticities, as these travelers are generally less sensitive to travel time.

The estimation results have different implications for decision makers. As outlined in the introduction, policymakers have various options to reduce the climate impact of the transportation sector. Beyond market-based measures like carbon taxes or an emissions trading system, regulatory instruments such as a SAF quota, along with infrastructure investments, offer alternative means to reduce emissions from aviation. Our results enable policymakers to assess the extent to which investment in HSR induce a modal shift away from air transport, potentially contributing to climate change mitigation. Furthermore, by utilizing the calculated price elasticities from our results, it is possible to simulate the effects on demand of any increase in airfares that arises from market-based measures such as ticket taxes or emissions trading schemes. However, policy measures aimed at reducing emissions by inducing a modal shift from one transport mode to another are only effective as long as the emissions per passenger kilometre of these modes differ (substantially) also in the long-term. This consideration is especially crucial given the substantial planned investments in HSR networks in many countries.

For example, in Germany, the Deutschlandtakt (Germany schedule) envisages a further reduction in travel times on many routes through expansion of HSR sections. In particular, for the entire route between Cologne/Düsseldorf and Berlin, a further 9.8 % reduction in travel time is planned. This corresponds to a 10.8 % increase in average train travel speed and could shift, based on the lower and upper bounds of our parameter estimates for domestic routes and routes longer than 344 km (−0.434 and −0.796, see Tables 6 and 8), between 4.7 % and 8.6 %, or approximately 122,000 to 224,000 annual air trips to rail. According to UBA (2021), domestic air travel in Germany emits 218 g of CO_2e per passenger kilometer, while high-speed rail emits nearly 80 % less per passenger kilometer (46 g CO_2e). These figures include emissions from both transport operations and infrastructure construction. Over the distance of 477 km between Cologne/Düsseldorf and Berlin, this translates into annual emission savings of between 10,000 and 18,400 tons of CO_2e.[7]

On the other hand, alternative energy carriers like synthetic aviation fuels, so-called power-to-liquid or e-fuels, can also achieve up to or even exceed an 80 % reduction in life-cycle CO_2 emissions, while also mitigating other non-CO_2 effects compared to conventional kerosene. Moreover, sustainable aviation fuels can be used without complex

[7] In 2019, rail travel time between Cologne/Düsseldorf and Berlin was 258 min. A total of 2.6 million passengers travelled on the two routes by air (vice versa). A 9.8% reduction in rail travel time raises average speed from 111 km/h to 123 km/h (a 10.8% increase). The reduction in air passengers is estimated by applying this speed increase to regression-based train speed parameters and passenger numbers. CO_2 savings are calculated by multiplying the number of passengers switching to rail by the per-passenger savings of 82 kg CO_2e (172 g CO_2e × 477 km).

infrastructure or aircraft adjustments. However, their widespread adoption is currently constrained by limited production capacities and considerably higher costs relative to fossil fuels (Braun et al., 2024). In 2025, the EU therefore introduced an obligatory mandate for the usage of sustainable aviation fuels to increase both demand and supply. In the future, the development of the prices and accessibility of alternative energy carriers in aviation will be crucial for prioritising decarbonisation options and weighing up mitigation alternatives.

7. Conclusion

This paper investigates the impact of a reduction in travel times in German domestic and cross-border rail transport on the number of air passengers. Our empirical approach is based on a structural gravity model that is estimated using PPML. By transferring this approach from the recent empirical trade literature to the interaction between air and rail transport, we demonstrate its usefulness for similar research questions. The results show that for city-pair connections with a distance of less than 800 km, a 1 % increase in rail travel speed leads on average to about a 0.6 % decrease in the number of air passengers. This effect is even more pronounced for German domestic routes, shorter distances and business class passengers, with reductions of over 0.7 % and over 2 % respectively. For cross-border connections only, the effect though is insignificant. Our further estimates indicate that the existence of a night train connection has the potential to additionally reduce aviation demand by up to between 10 % to 36 %, with stronger impacts on international connections. The price elasticities obtained by various forms of our regressions are below −0.4 in absolute terms, suggesting a low price sensitivity of air travellers on the analysed routes, especially on very short distances under 344 km. This observation may be attributed to the predominantly business-related nature of short-haul intra-German air travel. As expected, the presence of LCCs increases the number of air passengers, while higher market concentration, as measured by the HHI, leads to a reduction in air travel numbers.

Our results provide insights for policymakers seeking to assess the extent to which investments in HSR can encourage a modal shift to rail transport. Such a shift has the potential to reduce carbon emissions and contribute to climate change mitigation goals, particularly in regions where rail offers a more sustainable alternative for short- and medium-distance travel over other modes of transport. In the future, sustainable aviation fuels may offer an additional pathway for reducing emissions from aviation, potentially achieving emissions reductions comparable to those from a modal shift to high-speed rail, and especially on longer routes where rail is less competitive. In addition to the relevance for policymakers, our results also have implications for industry stakeholders. Airports and airlines can use them to better assess the impact of current and planned rail infrastructure projects on future demand at individual airports or on individual flight routes.

CRediT authorship contribution statement

Katrin Oesingmann: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **David Ennen:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Data curation, Conceptualization.

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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References

Adler, N., Pels, E., Nash, C., 2010. High-speed rail and air transport competition: Game engineering as tool for cost-benefit analysis. Transp. Res. B Methodol. 44 (7), 812–833. https://doi.org/10.1016/j.trb.2010.01.001.

Albalate, D., Bel, G., Fageda, X., 2015. Competition and cooperation between high-speed rail and air transportation services in Europe. J. Transp. Geogr. 42, 166–174. https://doi.org/10.1016/j.jtrangeo.2014.07.003.

Anderson, J.E., van Wincoop, E., 2003. Gravity with Gravitas: a solution to the Border Puzzle. Am. Econ. Rev. 93 (1), 170–192. https://doi.org/10.1257/000282803321455214.

Baier, S.L., Bergstrand, J.H., 2007. Do free trade agreements actually increase members' international trade? J. Int. Econ. 71 (1), 72–95. https://doi.org/10.1016/j.jinteco.2006.02.005.

Berster, P., Pabst, H., Wilken, D., Decker, H., Kuhne, M., 2019. DLR-Low Cost Monitor (Reports 1/2006–2/2019).

BMDV, n.d. Projektinformationssystem zum Bundesverkehrswegeplan 2030, Projekt Nr. 2-016-V02 [Project information system for the Federal Transport Infrastructure Plan 2030, Project No. 2-016-V02]. Bundesministerium für Digitales und Verkehr. https://bvwp-projekte.de/schiene_2018/2-016-V02/2-016-V02.html.

BMVI, 2016. Bundesverkehrswegeplan 2030 [Federal Transport Infrastructure Plan 2030]. Bundesministerium für Verkehr und Digitale Infrastruktur.

Brand, C., Sieg, G., 2020. The impact of delays on the welfare effects of on-track competition: the case of transfer passengers with operator-tied tickets. Res. Transp. Econ. 80, 100801. https://doi.org/10.1016/j.retrec.2019.100801.

Braun, M., Grimme, W., Oesingmann, K., 2024. Pathway to net zero: reviewing sustainable aviation fuels, environmental impacts and pricing. J. Air Transp. Manag. 117, 102580. https://doi.org/10.1016/j.jairtraman.2024.102580.

Castillo-Manzano, J.I., Pozo-Barajas, R., Trapero, J.R., 2015. Measuring the substitution effects between High speed Rail and air transport in Spain. J. Transp. Geogr. 43, 59–65. https://doi.org/10.1016/j.jtrangeo.2015.01.008.

Chen, Z., 2017. Impacts of high-speed rail on domestic air transportation in China. J. Transp. Geogr. 62, 184–196. https://doi.org/10.1016/j.jtrangeo.2017.04.002.

Clewlow, R.R., Sussman, J.M., Balakrishnan, H., 2014. The impact of high-speed rail and low-cost carriers on European air passenger traffic. Transp. Policy 33, 136–143. https://doi.org/10.1016/j.tranpol.2014.01.015.

Conte, M., Cotterlaz, P., Mayer, T., 2022. The CEPII Gravity Database. CEPII Working Paper 2022-05.

Correia, S., 2023. IVREGHDFE: reghdfe + ivreg2. https://github.com/sergiocorreia/ivreghdfe?tab=readme-ov-file#usage (accessed 11 November 2024).

Correia, S., Guimarães, P., Zylkin, T., 2020. Fast Poisson estimation with high-dimensional fixed effects. Stata J. 20 (1), 95–115. https://doi.org/10.1177/1536867X20909691.

Cristea, A.D., Hillberry, R., Mattoo, A., 2015. Open Skies over the Middle East. World Econ. 38 (11), 1650–1681. https://doi.org/10.1111/twec.12314.

D'Alfonso, T., Jiang, C., Bracaglia, V., 2015. Would competition between air transport and high-speed rail benefit environment and social welfare? Transp. Res. B Methodol. 74, 118–137. https://doi.org/10.1016/j.trb.2015.01.007.

Dobruszkes, F., 2011. High-speed rail and air transport competition in Western Europe: a supply-oriented perspective. Transp. Policy 18 (6), 870–879. https://doi.org/10.1016/j.tranpol.2011.06.002.

European Environment Agency, 2022. Transport and environment report 2022: Digitalisation in the mobility system: challenges and opportunities.

Feenstra, R.C., 2004. Advanced International Trade: Theory and evidence. Princeton University Press, Princeton, NJ, p. 484.

Grahnert, M., Krings, M., 2023. Datenbank Fernverkehr [Long-distance rail database]. https://www.fernbahn.de/ (accessed 8 December 2023).

International Union of Railways, 2023. High-speed data and atlas. accessed 30 November 2023. https://uic.org/passenger/highspeed/article/high-speed-data-and-atlas.

Jiménez, J.L., Betancor, O., 2012. When trains go faster than planes: the strategic reaction of airlines in Spain. Transport Policy 23, 34–41. https://doi.org/10.1016/j.tranpol.2012.06.003.

Jorge-Calderón, J.D., 1997. A demand model for scheduled airline services on international European routes. Journal of Air Transport Management 3 (1), 23–35. https://doi.org/10.1016/S0969-6997(97)82789-5.

Li, J., Sun, X., Cong, W., Miyoshi, C., Ying, L.C., Wandelt, S., 2024. On the air-HSR mode substitution in China: from the carbon intensity reduction perspective. Transportation Research Part a: Policy and Practice 180, 103977. https://doi.org/10.1016/j.tra.2024.103977.

Morlotti, C., Cattaneo, M., Malighetti, P., Redondi, R., 2017. Multi-dimensional price elasticity for leisure and business destinations in the low-cost air transport market: evidence from easyJet. Tourism Management 61, 23–34. https://doi.org/10.1016/j.tourman.2017.01.009.

Mumbower, S., Garrow, L.A., Higgins, M.J., 2014. Estimating flight-level price elasticities using online airline data: a first step toward integrating pricing, demand,

and revenue optimization. Transportation Research Part a: Policy and Practice 66, 196–212. https://doi.org/10.1016/j.tra.2014.05.003.

Oesingmann, K., 2022a. The determinants of air cargo flows and the role of multinational agreements: an empirical comparison with trade and air passenger flows. The World Economy 45 (8), 2370–2393. https://doi.org/10.1111/twec.13245.

Oesingmann, K., 2022b. The effect of the European Emissions Trading System (EU ETS) on aviation demand: an empirical comparison with the impact of ticket taxes. Energy Policy 160, 112657. https://doi.org/10.1016/j.enpol.2021.112657.

Olivero, M.P., Yotov, Y.V., 2012. Dynamic gravity: endogenous country size and asset accumulation. Canadian J of Economics 45 (1), 64–92. https://doi.org/10.1111/j.1540-5982.2011.01687.x.

Pagliara, F., Vassallo, J.M., Román, C., 2012. High-speed Rail versus Air Transportation: Case Study of Madrid–Barcelona. Spain. Transportation Research Record 2289 (1), 10–17. https://doi.org/10.3141/2289-02.

Park, Y., Ha, H.-K., 2006. Analysis of the impact of high-speed railroad service on air transport demand. Transportation Research Part e: Logistics and Transportation Review 42 (2), 95–104. https://doi.org/10.1016/j.tre.2005.09.003.

Piermartini, R., Rousová, L., 2013. The Sky is not flat: how Discriminatory is the Access to International Air Services? American Economic Journal: Economic Policy 5 (3), 287–319. https://doi.org/10.2307/43189348.

Román, C., Espino, R., Martín, J.C., 2007. Competition of high-speed train with air transport: the case of Madrid–Barcelona. Journal of Air Transport Management 13 (5), 277–284. https://doi.org/10.1016/j.jairtraman.2007.04.009.

Sabre,, 2023. Sabre Market Intelligence. accessed 31 March 2023. https://www.sabre.com/products/suites/pricing-and-revenue-optimization/market-intelligence/.

Santos Silva, J., Tenreyro, S., 2006. The Log of Gravity. Review of Economics and Statistics 88 (4), 641–658. https://doi.org/10.1162/rest.88.4.641.

Santos Silva, J., Tenreyro, S., 2011. Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator. Economics Letters 112 (2), 220–222. https://doi.org/10.1016/j.econlet.2011.05.008.

Socorro, M.P., Viecens, M.F., 2013. The effects of airline and high speed train integration. Transportation Research Part a: Policy and Practice 49, 160–177. https://doi.org/10.1016/j.tra.2013.01.014.

Steer Davies Gleave, 2006. Air and Rail Competition and Complementarity: Final Report. Prepared for European Commission DG TREN.

UBA, 2021. Ein ökologischer Verkehrsartenvergleich für den Personen- und Güterverkehr in Deutschland [An ecological comparison of modes of transport for passenger and freight transport in Germany].

Wan, Y., Ha, H.-K., Yoshida, Y., Zhang, A., 2016. Airlines' reaction to high-speed rail entries: Empirical study of the Northeast asian market. Transportation Research Part a: Policy and Practice 94, 532–557. https://doi.org/10.1016/j.tra.2016.10.014.

Wang, K., Xia, W., Zhang, A., Zhang, Q., 2018. Effects of train speed on airline demand and price: Theory and empirical evidence from a natural experiment. Transportation Research Part b: Methodological 114, 99–130. https://doi.org/10.1016/j.trb.2018.05.017.

Yang, H., Burghouwt, G., Wang, J., Boonekamp, T., Dijst, M., 2018. The implications of high-speed railways on air passenger flows in China. Applied Geography 97, 1–9. https://doi.org/10.1016/j.apgeog.2018.05.006.

Yotov, Y., Piermartini, R., Monteiro, J.-A., Larch, M., 2016. An Advanced Guide to Trade Policy Analysis: the Structural Gravity Model. World Trade Organization.

Yu, K., Strauss, J., Liu, S., Li, H., Kuang, X., Wu, J., 2021. Effects of railway speed on aviation demand and CO2 emissions in China. Transportation Research Part d: Transport and Environment 94, 102772. https://doi.org/10.1016/j.trd.2021.102772.

Yuan, Z., Dong, C., Ou, X., 2023. The substitution effect of high-speed rail on civil aviation in China. Energy 263, 125913. https://doi.org/10.1016/j.energy.2022.125913.

Zhang, Q., Yang, H., Wang, Q., 2017. Impact of high-speed rail on China's big three airlines. Transportation Research Part a: Policy and Practice 98, 77–85. https://doi.org/10.1016/j.tra.2017.02.005.

Zhang, Y., Zhang, A., 2016. Determinants of Air Passenger Flows in China and Gravity Model: deregulation, LCC and High speed Rail. Journal of Transport Economics and Policy 50 (3), 287–303. https://doi.org/10.2139/ssrn.2775501.