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Mario Liebensteiner, Jakob Losert, Sarah Necker, Florian Neumeier, Jörg Paetzold, Sebastian Wichert

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Almost Fare Free: Impact of a Cheap Public Transport Ticket on Mobility Patterns and Infrastructure Quality

Abstract

In 2022, Germany introduced a temporary 9-euro monthly ticket for unlimited local and regional public transport. We investigate its impact on mobility patterns, including increased public transport usage, reduced car traffic, and rail network congestion. Using difference-in-difference and event-study analyses with mobile network-based mobility, traffic volume, and rail traffic data, we find limited substitution between transportation modes, a strong increase in leisure train journeys, and notable adverse effects on rail infrastructure quality. These effects dissipate after the ticket's expiration. Our study suggests caution regarding the expected environmental benefits of nearly fare-free 'go-anywhere' public transport tickets, which are discussed in several countries.

JEL-Codes: R120, R410, R420, R480, Q580.

Keywords: fare-free public transport, mobility patterns, traffic volume, mode choice, transport subsidies.

Mario Liebensteiner
Friedrich-Alexander-University Erlangen-Nürnberg (FAU) & Energy Campus Nürnberg / Germany
mario.liebensteiner@fau.de

Jakob Losert
University of Salzburg / Austria
jakob.losert@plus.ac.at

Sarah Necker
Friedrich-Alexander-University Erlangen-Nürnberg (FAU) & ifo Institute Fürth / Germany
necker@ifo.de

Florian Neumeier
ifo Institute Munich / Germany
neumeier@ifo.de

Jörg Paetzold
University of Salzburg / Austria & Liechtenstein Institute / Liechtenstein
joerg.paetzold@plus.ac.at

Sebastian Wichert
ifo Institute Munich / Germany
wichert@ifo.de

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1 Introduction

In recent years, several European countries and cities have discussed or introduced highly discounted or fare-free 'go-anywhere' tickets for public transportation. For instance, Luxembourg offers free public transportation since 2020. In 2021, Austria launched its 'Klimaticket', allowing buyers to use all public transport for 1,095 euros per year. Furthermore, large U.S. metropolitan areas such as Seattle, New York City or San Francisco are currently considering free-fare public transport, or have piloted zero-fare programs for certain groups (see, e.g., Brough et al., 2022). From June to August 2022, Germany became the first large-area country to introduce such a ticket on a universal scale, reducing the fare for all local and regional public transport nationwide to a flat rate of 9 euros per month. A policy goal of this (almost) fare-free public transport ticket was to encourage people to shift away from car to train travel and thus, help decarbonize the transportation sector.

In this study, we examine whether this so-called 9-Euro Ticket induced a shift in mobility patterns such as mode choice, and if it affected the quality of the public transport infrastructure. The treatment of the ticket policy was substantial, resulting in very large fare reductions. To give an example, the regular monthly fare for public transportation in the city of Hamburg was 112.80 euros, i.e., a reduction of 92% was achieved with the introduction of the ticket (ADAC, 2021). Theoretically, lower fare prices may have two effects: (i) substitution of car mobility for public transport, and (ii) generation of additional trips that were previously not taken. However, it could also be that the increase in demand was modest and the ticket mostly presented a windfall to those already using public transport. Overall, there is only very limited knowledge about how fare-free tickets encourage public transport use, and even less is understood about their impact on other travel modes or overall mobility.

We utilize various datasets to examine the effects of the 9-Euro Ticket. First, we analyze mobility data from mobile network devices (e.g., cellphones, smartwatches, tablets), enabling us to differentiate between different modes of transportation. Second, we leverage administrative traffic volume data from road monitoring stations to gain a comprehensive understanding of changes in car traffic. Third, we examine rail traffic data to consider potential adverse effects of the ticket, such as a decline in the quality of public transport due to train delays. We compare differences in outcomes between 2022 and 2019 using a difference-in-differences (DiD) approach and an event-study design. To disentangle the effect of the 9-Euro Ticket from other confounding factors, our empirical models include relevant control variables, such as weather conditions, holidays, and school vacations, and incorporate a comprehensive set of location- and time- fixed effects.

Our results indicate a large and significant increase in public transport usage across Germany, with the number of train trips rising by as much as 35%. In contrast, we only observe small effects of the 9-Euro Ticket on transport mode substitution. Following the introduction of the ticket, we observe a statistically significant reduction in car traffic between 1-5%, depending on the measure and dataset we use. Furthermore, the influx of additional train passengers caused by the 9-Euro Ticket resulted in a significant increase in train delays. This indicates an adverse effect on infrastructure quality. All effects we observe dissipate after the expiration of the 9-Euro Ticket in September 2022, indicating no lasting changes in transportation mode.

Studying effect heterogeneity, we find larger increases in train trips on weekends and towards touristic destinations. Correspondingly, reductions in car traffic are the smallest during peak commuting times and at roads/stations which are predominantly frequented by commuter traffic. A series of placebo and robustness tests support and strengthen our results. Furthermore, we discuss how a confounding policy during our treatment period in the form of a fuel tax break may affect our results. Through a back-of-the-envelope calculation, we demonstrate that the estimation bias is likely to be low.

Our results have important policy implications. Our study indicates that while this (almost) fare-free, country-wide public transport ticket led to increased public transport usage, it appeared not very effective in inducing mode substitution away from car traffic. Furthermore, the results suggest that the increased public transport usage was particularly driven by leisure use. In contrast, (car) commuter traffic seems to be much less responsive to these fare-free ticket schemes. Therefore, policymakers aiming to decarbonize the transportation sector may consider other measures than (almost) fare-free go-anywhere tickets to induce changes in transportation modes. Nonetheless, it is possible that the policy was successful in alleviating cost-of-living strains for public transport users.

Our study complements the economic literature on mobility substitution incentives, including their intended and adverse consequences. Some studies assess public transportation strikes to infer substitution between private and public transport. Bauernschuster et al. (2017) find increased car usage, more road traffic accidents, elevated air pollution, and adverse health effects related to short-term public transport strikes in Germany. Anderson (2014) provides evidence of significantly increased road congestion during a 35-day public transport strike in Los Angeles.

Besides these arguably more extreme cases where one mode of transportation is essentially shut down, substitution effects are usually found to be much smaller. Chen and Whalley (2012) find little evidence for travel substitutions between car and rail in response to the opening of a major metro line in Taipei. More generally, Beaudoin and Lawell (2018) find across 96 urban areas in the U.S. that increases in public transit supply can reduce car traffic, but that the substitution elasticity is low. In the long run, a 10% increase in transit capacity is associated with a 0.4% decrease in auto travel.[1]

Other studies investigate the effects of car driving restrictions. Zhang et al. (2019) show that car driving restrictions increase public transportation usage in six cities in China, whereas a mere license plate restriction policy had no significant effect. In a similar vein, Davis (2008) examines a one-weekday-per-week ban of car usage in Mexico City based on the last digit of the vehicle's license plate, and finds that the overall number of vehicles increased to circumvent the regulation. Gallego et al. (2013) studies different driving restrictions and public transport reforms in Latin American cities and observes sometimes adverse effects, with more cars on the road and varying responses among income groups. These studies highlight the challenges and complexities of implementing transportation policies in order to curb traffic. Another strand of literature focuses on air quality and health outcomes following public transport reforms such as low-emission zones, or changes in public transit supply (Currie and Walker, 2011; Knittel et al., 2016; Margaryan, 2021). For instance, Lalive et al. (2018) find that increasing rail service reduces air pollution. In a similar vein, Gendron-Carrier et al. (2022) find evidence for reduced particulate matter exhaust after openings of new subway systems.

Instead of bans, restrictions, or changes in the supply of public transit, most other public transport policies focus on changing relative prices between public and private transport to alter people's mode of transportation. However, the recovered fare elasticities are often estimated based on relatively small fare changes and vary widely depending on the magnitude and scope of the fare change (see, e.g., Holmgren, 2007, or Hörcher and Tirachini, 2021, for meta-studies on fare elasticities). Beyond that, evidence from large-scale (country-wide) fare-free public transport schemes is extremely scarce. The vast majority of such ticket schemes stem

[1]These empirical estimates are considerably smaller than what theoretical models and simulations sometimes predict; see, e.g., Basso and Silva (2014).

from single cities or metropolitan areas (see Kębłowski, 2020, for an overview). Other studies employ randomized controlled trials in which a randomly selected (often very small) group of individuals receives temporarily access to free public transport (Bull et al., 2021; Brough et al., 2022). In contrast, our study provides first evidence on the nationwide implementation of an (almost) fare-free ticket scheme, which makes it especially policy-relevant.

A few other studies have examined the effect of the 9-Euro Ticket. Gohl and Schrauth (2024) find improved air quality at urban air measurement stations after its implementation. This result seems inconsistent with our finding of only small reductions in car traffic. However, their findings are based on air measurement stations positioned on busy roads in urban city centers. In contrast, our study is based on data from all traffic monitoring stations across the entire country as well as mobility flows between all German counties. In addition, Andor et al. (2023) conducted an internet survey on self-reported car and public transport usage in April and June 2022 for Germany. In line with our study, they find little evidence for car-to-rail substitution but rather an expansion in personal mobility. However, while their study relies on self-reported survey responses that can be interpreted as stated preferences, our study uses observational data, focusing on revealed preferences. Furthermore, measuring mobility at only two points in time does not allow them for testing common trends, or studying dynamic behavioral responses to the ticket over time.

The remainder of the paper is structured as follows. Section 2 discusses the institutional setup in more detail. Section 3 presents the datasets employed, and Section 4 describes the empirical approach. Sections 5, 6, and 7 present the empirical results, including robustness tests, using datasets on mobile network-based mobility measures, traffic volumes, and train delays, respectively. Section 8 discusses threats to identification. Section 9 concludes.

2 Institutional Background

The 9-Euro Ticket was available from June, 1st, until August, 31st, 2022. It allowed its owners to use all buses, streetcars, and trains – including subway and suburban trains – operated by public transport companies nationwide for all connections. However, long-distance trains (e.g., Intercity Express trains, Intercity trains, Eurocity trains, etc.) were not covered by the 9-Euro Ticket. The ticket was sold on a monthly basis. Fifty-two million tickets were bought over the duration of the three months, plus ten million tickets automatically handed out to subscribers of monthly public transport passes (VDV, 2022).

The 9-Euro Ticket implied a substantial fare reduction. Monthly ticket holders as well as non-monthly ticket holders could benefit. Since prices and coverage of the monthly subscription tickets vary between German cities, the fare reduction for ticket holders was not uniform. A comparison of 21 large German cities in 2021 reveals notable differences in public transportation fare prices (ADAC, 2021). The highest monthly fare was 112 euros, and the average monthly fare across these cities was 80 euros. In addition, it has to be considered that the nationwide coverage of the 9-Euro Ticket significantly exceeded that of the usual monthly tickets for local regions. Furthermore, for non- subscribers (which constitute vast majority of public transport users in Germany), the fare reduction obviously depends on the distance and frequency of trips.

The motivation for the introduction of the 9-Euro Ticket was twofold. On the one hand, the goal was to cushion rising living costs in the aftermath of the Russian war against Ukraine, which led to an increase in the cost of energy, food, heating, and mobility. On the other hand, the aim was to increase the use of public transportation. More specifically, the 9-Euro Ticket was featured as an instrument to foster the decarbonization of the transportation sector. Especially the Green Party, which has been part of the federal government since 2021, were strong proponents of an affordable go-anywhere ticket to fight climate change. Thus, the 9-Euro Ticket became part of a larger package to combat rising transportation costs. This package included a tax break on fuels during the same period ("Tankrabatt"). Section 8.1 provides a discussion on the potential effect of this tax cut on our estimation strategy.[2]

3 Data

In our empirical analysis, we assess outcomes during the treatment period relative to a pre-treatment period, where the year 2022 serves as the treatment group and the year 2019 serves as the control group. For consistency and to reduce noise from higher data frequency, we aggregate all datasets to the weekly level.

For our analysis, we compare the months May through September of the treatment year 2022 with the same months in 2019. We did not take the years 2020 and 2021 into consideration

[2]Another potentially relevant measure is an increase of tax deductions for long-distance commuters, which was decided in mid-may 2022 and became effective as of 1.1.2022. However, the tax deduction can be used for all types of transportation. Another component of the relieve packages were lump-sum payments to different groups (“Energiepreispauschale”), which were however only paid after August 2022.

because of the various and changing COVID-19 restrictions during these years.

Given that some of the data we use is proprietary which we needed to pay for, our research budget allowed us to purchase 5 months of data in each year. Given that some COVID-19 restrictions were still prevalent during the early months of 2022, we decided to purchase data for one month prior to the treatment (May), the treatment period (June through August), and one month after the treatment (September). Only in April 2022, central restrictions were lifted in Germany. Importantly, during our observation period from May to September 2022, COVID-19 restrictions remained basically constant, as shown in Appendix Figure A.2. Given that COVID-19 restrictions did not change between the pre-treatment and post-treatment period in 2022, our DiD approach disentangles any related effects from the treatment effect.

3.1 Mobile Network-based Mobility Data

We purchased proprietary mobile network-based mobility data from Teralytics.[3] The dataset indicates the number of trips made between a starting location and a destination from May to September in both 2019 and 2022, recorded at an hourly frequency. The data distinguish between the transport modes of train and road.

Consequently, an observation is defined as the number of trips made from location A to location B using the mode of transport M (train or road) on day D (e.g., 31 May 2022) at hour H (e.g., between 2 pm and 3 pm). Thus, our data set has a panel structure with four dimensions: starting location, destination, mode of transport, and time. The starting location and destination of a trip can be any of the 401 counties in Germany or a foreign country, whereas a county can be both the starting location and the destination of a trip. This yields a total of $402^2 = 161,604$ starting location-destination pairs.

A trip is defined as a movement between a starting location and a destination if the mobile device user remained at the destination for at least 30 minutes. To track the movement of a mobile device user, Teralytics combines different pieces of information, such as the location of cell towers with which a mobile device is connected and the strength of the mobile device signal. For validation, a tracking technology is used on the mobile devices of a subset of users. The mode of transport used for a trip is identified by matching the movements of mobile device users with the routes of roads and rails. However, the mode of transport can only be reliably determined for trips that are at least 30 kilometers long. Trips shorter than 30 kilometers are not

[3] Further information about the data is provided at https://teralytics.net. The product code is DELDD1.

Table 1: Summary Statistics – Mobile Network-based Mobility Data

Panel A: Descriptive statistics per starting-destination pair and week						
	Train trips			Road trips		
	Year 2019	Year 2022	Total	Year 2019	Year 2022	Total
Observations	1,972,951	1,652,412	3,625,363	4,032,897	3,806,539	7,839,436
Mean	115.6	126.2	120.4	455.5	389.9	423.6
Std. Dev.	963.2	887.0	929.3	2584.3	2179.3	2396.4
Panel B: Descriptive statistics per week, national aggregates						
	Train trips			Road trips		
	Year 2019	Year 2022	Total	Year 2019	Year 2022	Total
Observations	27	27	54	27	27	54
Mean	8,444,123.6	7,724,663.3	8,084,393.5	68,030,103.7	54,963,103.1	61,496,603.4
Std. Dev.	1,128,902.9	2,200,228.1	1,769,708.3	9,470,370.1	9,880,320.8	11,635,260.9

Notes: Panel A shows descriptive statistics for road and train trips, respectively, for all pairs of a starting and a destination county and week. Panel B shows descriptive statistics for the number of train and road trips for Germany as a whole per week. Columns headed 'Year 2019' show the number of observations, the weekly average number of train and road trips, and their standard deviations for May to September 2019, columns headed 'Year 2022' for May to September 2022. The column headed 'Total' contain the number of observations, average numbers of train and road trips, and standard deviations for our whole sample period.

included in our dataset. Consequently, our data likely do not cover the majority of inner-city traffic.

To determine the number of trips between two locations, Teralytics uses data from the mobile network provider Telefónica and extrapolates them to the entire German population based on socio-demographic characteristics of cellphone users.[4] To ensure the anonymity of mobile device users, instances in which less than 5 persons were traveling between two locations at a certain hour of a certain day are excluded from our data set, which is why our panel data is slightly unbalanced.

Table 1 presents descriptive statistics for the mobile network-based mobility data. Panel A of Table 1 provides information at the level of starting-destination county pairs and weeks, which corresponds to the unit of analysis in our DiD and event-study estimations. Panel B presents aggregated statistics at the national level per week. Overall, the our empirical analysis is based on roughly 69.5 million trips per week, of which, on average, 8.0 million trips were made by train and 61.5 million were road trips (see the columns with the heading 'Total' in Panel B of Table 1).

Interestingly, both the average number of train trips and the average number of road trips

[4]In 2022, Telefónica had a market share of 28.2%. Besides Telefónica, there are only two other mobile network providers in Germany, namely Telekom and Vodafone. For information on quality and representativeness of the underlying mobile network data see the workshop report of the Federal Statistical Office of Germany (https://www.destatis.de/EN/Service/EXSTAT/Datensaetze/mobile-network-operators.html).

per week decreased from 2019 to 2022. While, on average, 8.4 million trips were made by train in 2019 per week, this figure fell to 7.7 million in 2022. At the same time, the number of roads trips decreased from 68 million per week in 2019 to 59 million per week in 2022. One possible explanation is a lasting shift to working from home caused by the Corona pandemic. The average number of train trips between any two counties in Germany is 120 per week, the average number of road trips is 423 (cf. column 'Total' in Panel A of Table 1).

3.2 Traffic Volume Data

As mentioned above, a limitation of the mobile network-based mobility dataset is that it only captures trips of more than 30km. Therefore, we complement this dataset with data on traffic volumes provided by the Federal Highway Research Institute (BASt, 2022). Inductive loops embedded in the road pavement measure the daily number of passenger vehicles and trucks passing a monitoring station. Thus, traffic volume is recorded irrespective of the length of the trip. In total the traffic volume data stems from 2,095 monitoring stations installed on highways and freeways. Figure A.3 in the Appendix shows a map with the location of all monitoring stations. The map indicates a dense net of monitoring stations across Germany, with a concentration of stations in and around metropolitan areas.

Table 2 presents descriptive statistics for the traffic volume data, showing the average weekly number of passenger vehicles recorded across all traffic stations. We find that, on average, around 200,000 passenger vehicles are recorded per station. Furthermore, we observe somewhat less traffic in 2022 compared to 2019.

Table 2: Summary Statistics – Traffic Volume Data

	Year 2019	Year 2022	Total
Observations	31,284	31,284	62,568
Mean	208,611.6	190,294.1	199,452.9
Std. Dev.	197,574.9	180,417.5	189,410.9

Notes: The table shows descriptive statistics from all traffic volume monitoring stations across Germany. It displays the weekly average number of passenger vehicles measured per monitoring station.

Table 3: Summary Statistics – Train Delay Data

	All trains			Regional trains			Long-distance trains		
	Year 2019	Year 2022	Total	Year 2019	Year 2022	Total	Year 2019	Year 2022	Total
Observations	72,201	54,244	126,445	71,995	48,055	120,050	7,199	19,192	26,391
Mean	0.074	0.114	0.092	0.071	0.088	0.078	0.216	0.258	0.246
Std. Dev.	0.103	0.149	0.126	0.102	0.114	0.107	0.181	0.249	0.233

Notes: The table shows descriptive statistics for the train delay data. Columns headed 'Year 2019' show the number of observations, the weekly average share of train delays (≥ 6 min.) per station, and their standard deviations for May to September 2019, columns headed 'Year 2022' for May to September 2022. The column headed 'Total' contain the number of observations, weekly average share of train delays, and standard deviations for our whole sample period.

3.3 Train Delay Data

We bought proprietary data on scheduled and actual train arrivals from the online platform "zugfinder.de" ("train finder"). The data encompass all passenger train trips arriving at German train stations and cover the period May through September of the years 2019 and 2022. The data distinguish between regional trains, for which the 9-Euro Ticket was eligible, and long-distance trains.

Even though long-distance trains were not covered by the 9-Euro Ticket, spillover effects are likely, and thus subject of investigation in this study. On the one hand, some passengers may have substituted journeys via long-distance trains for the almost fare free regional trains, thereby relieving long-distance trains. On the other hand, it is likely that more train passengers in the regional train segment may have led to network congestion, thereby adversely affecting long-distance trains.

In total the data cover 3,445,875 regional train trips and 355,577 long-distance train trips. For those trips, we have 25,258,640 data points on train arrivals per German train station per day. Unfortunately, train cancellations are not indicated in the data. Therefore, it is not clear where or when a train ceased operation (e.g., due to a too long delay) or terminated according to schedule. For this reason, we can only infer about delays as long as a train is in operation.

The state-owned national railway company of Germany, Deutsche Bahn AG, reports a train as delayed if it arrives a station six minutes or later than scheduled. For the empirical analysis, we aggregated the data to the station level and weekly frequency. Our primary focus lies on the extensive margin, where we examine the proportion of trains per station experiencing delays of six minutes or more. Additionally, we also conduct a regression analysis on the intensive margin, which is measured as the average train delay in minutes per station.

Table 3 provides summary statistics for the train delay data. The data refer to the share of delayed trains per station per week. On average, 9.2% of the trains are delayed. While in 2019 7.4% of the trains were delayed, the share rose to 11.4% in 2022. Regional trains are significantly less delayed (7.8% on average) than long-distance trains (24.6% on average). Our data also show a high consistency with official statistics reported by Deutsche Bahn AG (DB, 2022).[5]

Finally, we utilize a database provided by Deutsche Bahn AG (DB, 2020) to incorporate information about the federal state in which each train station is located. This step is crucial for merging state-specific holiday and vacation data, as well as meteorological data such as precipitation and temperature.

3.4 Data on Covariates

Meteorology Data — In order to control for the potential effect of weather conditions on mobility and the choice of transport mode, we gathered data on temperature and precipitation from all German weather stations operated by the German Weather Service (DWD, 2022). We aggregate the daily data to weekly averages. For the mobile network-based mobility data, we use weather stations located within the respective county, and if multiple stations are present, we calculate mean values. For the traffic volume data, we assign the closest weather station to the respective traffic monitoring station. For the train delay data, we utilize average temperature and precipitation at the federal state level, since only the federal state of each train station is known.

Fuel Price Data — We gathered data from Tankerkönig (2023) to control for fuel prices. We calculate weighted fuel prices using the ratio of gasoline to diesel cars registered in Germany and aggregate the fuel prices to a weekly average per gas station. When analyzing the mobile network-based mobility data, we take the average of all gas station prices in the respective county. For the traffic volume data, we assign the price of the closest gas station to the respective traffic monitoring station. For the train delay data, we use average gas station prices at the federal state level. Appendix Figure Figure A.1 shows the development of the weighted average daily fuel price from January 1 to October 31, 2022.

[5]The discrepancy between the official punctuality data reported by DB (2022) and our dataset is likely due to the fact that our data only cover the months from May through September, rather than the entire year.

Holiday and Vacation Data — Mobility differs on holidays and during school vacations. To control for this, we use data on holidays and school vacations at the state level from Kalenderpedia (2023). We create a dummy variable that equals one if a respective week contains a public holiday. Furthermore, we create an impulse dummy variable equal to one only for the week in which school vacations start, and a dummy variable equal to one for each week that falls within a school vacation period.

4 Empirical Approach

4.1 Difference-in-Difference Estimation

To evaluate the overall effects of the 9-Euro Ticket, we start with a standard difference-in-difference (DiD) estimation over the validity period of the 9-Euro Ticket (June-August 2022). The exact specification of the empirical model that we estimate depends on the outcome variable.

Mobile network-based mobility data — When using the number of train/road trips as outcome variables – which vary over origin-destination pairs and time – our DiD specification looks as follows:

$$Y_{odwy} = \eta_{od} + \theta_y + \alpha_w + \beta_{treat} \cdot D_{treat} + \beta_{post} \cdot D_{post} + \gamma \mathbf{X}_{owy} + \delta \mathbf{X}_{dwy} + \varepsilon_{odwy} \tag{1}$$

The index o refers to the origin district and d to the destination district of a trip.

The outcome variable Y_{odwy} measures how many trips were made from district o to district d in week w of year y (o refers to the origin and d to the destination district of a trip). We estimate Equation 1 separately for each mode of transportation (i.e. train or road). In addition, we control for weather conditions, holidays and vacations in both the origin district (vector $\mathbf{X}_{owy}$) and the destination of a trip (vector $\mathbf{X}_{dwy}$). η_{od} is a fixed effect that varies across origin-destination district pairs. It captures time-invariant characteristics like the distance between districts or traffic connections. θ_y is a year-fixed effect and α_w a week-of-the-year-fixed effect. D_{treat} represents our treatment dummy, taking a value of 1 from the first week of June to the last week of August 2022, and 0 otherwise. D_{post} indicates the post-treatment period, equaling 1 during the weeks in September 2022. The main coefficient of interest, β_{treat}, measures the change in mobility from May 2022 to June through August 2022, relative to the same period in our base year 2019. This approach allows us to account for seasonal differences. The standard errors ε are clustered at the origin and the destination level. The regressions are weighted by the average number of trips per origin-destination pair in 2019, placing emphasis on heavily traveled routes.

Road traffic volume data & train delay data — When using traffic volume data or train delay data as the outcome variables, the DiD estimation takes the following form:

$$Y_{swy} = \eta_{sy} + \alpha_w + \beta_{treat} \cdot D_{treat} + \beta_{post} \cdot D_{post} + \gamma \mathbf{X}_{swy} + \varepsilon_{swy} \quad (2)$$

Regarding road traffic volume data, the outcome variable Y_{swy} measures the traffic volume measured at station s in week w of year y. Regarding train delay data, Y_{swy} refers to the share of delayed train arrivals per train station (s), per week(w) per year(y). D_{treat} indicates the weeks of the treatment period June through August, while D_{post} indicates the weeks of the post-treatment period in September 2022. The coefficient of interest, β_{treat}, measures the change in traffic volume or the share of delayed trains from May 2022 to June through August 2022, relative to the same period in our base year 2019, which allows us to account for seasonal differences.

η_{sy} are station-year-fixed effects which we include to capture time-invariant station-specific characteristics. Regarding traffic volumes, η_{sy} may capture, for instance, the number of lanes per monitoring station or the distance to a rail station. Concerning train delays, η_{sy} might capture the number of platforms per train station and its size. α_w denotes week-fixed effects through which we control for week-of-the-year fluctuations in traffic volumes or train delays. $\mathbf{X}$ is a set of control variables. Concerning traffic volumes, these include weather conditions, holidays, and vacations measured per station, week, and year. Regarding train delays, X also includes weather conditions, holidays, and vacations, and additionally the number of trains arriving per station. However, due to a lack of geo-coded information about the precise location of the train station, weather conditions are approximated by the average per federal state. The standard errors ε are clustered by station-year and week. The regressions are weighted by the average traffic frequency of each station in 2019 (i.e., the number of cars or the number of trains), placing emphasis on more frequented stations.

4.2 Event-Study Analysis

In addition to the DiD estimation, we also assess the effects of the 9-Euro Ticket on traffic-volume, mobility, and train-delay patterns using an event study approach. This approach allows us to track the effect of the 9-Euro Ticket dynamically over time and to test the validity of the common trend assumption, which is a prerequisite for the identification of causal effects (Schmidheiny and Siegloch, 2023).

Mobile network-based mobility data — When using our mobile network-based mobility data as the outcome variable, we estimate the following empirical model:

$$Y_{odwy} = \eta_{od} + \theta_y + \alpha_w + \sum_{w \neq x} \beta_w \cdot D^j_{w|y=2022} + \gamma \mathbf{X}_{owy} + \delta \mathbf{X}_{dwy} + \varepsilon_{odwy} \tag{3}$$

The event-study indicators $D^j_{w|y=2022}$ are dummy variables that are equal to 1 in week w of the year 2022 and 0 otherwise. We omit the indicator for the last week in May before the event date. This week then serves as our reference category. Consequently, the coefficients β_w measure the change in mobility between our base week x, which is the last week of May 2022, and week $w \neq x$ of 2022, relative to the same weeks in 2019. The remaining variables are defined as in Equation 1 and weighting follows the same principle.

Road traffic volume data & train delay data — Again, our empirical model looks very similar when using traffic-volume and train-delay data as the outcome variables:

$$Y_{swy} = \eta_{sy} + \alpha_w + \sum_{w \neq x} \beta_w \cdot D^j_{w|y=2022} + \gamma \mathbf{X}_{swy} + \varepsilon_{swy} \tag{4}$$

The outcome variable Y refers to the road traffic volume or the share of delayed trains. The $D^j_{w|y=2022}$ are defined as in Equation 3 and the remaining variables as in Equation 2. Weighting follows the same principle.

4.3 Transforming the Estimates into Percentage Effects

Since Equations 1 to 4 are specified in levels and not in logarithms, our treatment effect estimates measure treatment-induced absolute changes in the outcome variables. To obtain relative changes in traffic volumes and mobility patterns following the introduction of the 9-Euro Ticket, we convert our treatment effect estimates into measures of the percentage change in our outcomes. Following Kleven et al. (2021), we compute *counterfactual* realizations for our outcome variables over the treatment period (June to August 2022). These counterfactual realizations indicate how many car or train trips (or delays) would have occurred during this period if the 9-Euro Ticket had not been introduced.

For the DiD approach described in Section 4.1, we calculate this counterfactual the following: First, we estimate the predicted value of the outcome variable given the model specified in Equations 1 and 2. Next, we subtract the estimated treatment effect from the mean value of this prediction during the treatment period (June through August 2022). This provides us with the counterfactual value of the outcome variable, representing what it would have been if the 9-Euro Ticket had not been implemented. Finally, we divide our treatment effect estimate by this counterfactual value to obtain a percentage effect:

$$p\% = \frac{\hat{\beta}_{treat}}{E[\tilde{y}_{06-08/22}]} \tag{5}$$

$\hat{\beta}$ is our estimated treatment effect from Equations 1 and 2 and $E[\tilde{y}_{06-08/22}]$ is the average realization of the counterfactual outcome over the period from June to August 2022.

In our event-study approach described in Section 4.2, we apply a similar transformation to obtain estimates for the treatment-induced percentage changes in our outcome variables:

$$p\%_w = \frac{\hat{\beta}_w}{E[\tilde{y}_w]} \tag{6}$$

The $\hat{\beta}_w$ are the week-specific coefficient estimates of our event-study indicators (cf. Equations 3 and 4). The $\tilde{y}_w$ are week-specific counterfactual realizations of our outcome variables net of the contribution of our event-study indicators. Again, we obtain these counterfactuals based on the estimated coefficients of the control variables from Equations 3 and 4.

5 Results from Mobile Network-based Mobility Data

5.1 Baseline Results

First, we turn to the results for our mobile network-based mobility data. Table 4 shows the estimates from the DiD estimation (cf. Equation 1). The first column depicts the results when using the weekly number of train trips as the outcome variable, and the second column for the number of road trips. The first row shows the estimated effect of the 9-Euro Ticket on the

Table 4: Results from DiD Estimation: Mobility Data

	(1) Train	(2) Road
Treatment effect (number of trips)	122.461	-36.006
	[64.112,180.809]	[-53.855,-18.157]
Number of public holidays	-3.192	19.184
	[-35.516,29.133]	[-19.728,58.096]
Number of school vacation days	-4.715	-3.127
	[-10.218,0.789]	[-7.697,1.444]
School vacation (impulse dummy)	7.690	8.756
	[-9.427,24.806]	[-7.950,25.463]
Summer vacation (impulse dummy)	3.486	5.510
	[-12.297,19.269]	[-16.886,27.907]
Rainfall in origin county	-0.150	-0.321
	[-1.552,1.251]	[-2.277,1.635]
Temperature in origin county	-1.265	1.581
	[-4.396,1.866]	[-2.427,5.589]
Rainfall in destination county	0.186	-1.241
	[-2.204,2.576]	[-2.665,0.183]
Temperature in destination county	-1.965	-1.145
	[-7.213,3.283]	[-4.397,2.107]
September 2022 dummy	-20.673	-14.594
	[-46.951,5.606]	[-32.805,3.617]
Treatment effect (in %)	34.465	-5.124
Counterfactual	355.319	702.650
Observations	2,763,545	5,905,116

Notes: The table shows the results from difference-in-difference estimation (Equation 1). 99% confidence intervals in brackets. The row 'counterfactual' shows the predicted average number of trips between two locations that would have been made if the 9-Euro Ticket was not introduced (see Section 4.3 for details).

number of trips per week. The third last row shows the relative change in the number of trips measured in percent, as described in Equation 5 of Section 4.3.[6]

Our findings show that the 9-Euro Ticket had a sizable effect on the number of train trips. Between June and August 2022, on average 122 additional trips were made by train between any two locations per week. This corresponds to a relative increase of about 34%. Put differently, the number of people taking the train between two locations in a certain week would have been 34% lower if the 9-Euro Ticket had not been introduced. Extrapolating this result to the entire country based on the descriptive statistics from Table 1, suggests that the 9-Euro Ticket led to an increase in the passenger volume on trains by close to 430,000 people per day. It should be noted, however, that our mobile network-based mobility data only covers trips of at least 30 km. Consequently, this estimate might be interpreted as a lower bound.

At the same time, the introduction of the 9-Euro Ticket led to only a small but statistically

[6]Please note that the estimated counterfactuals shown in Table 4 are larger than the average number of train/car trips between two counties displayed in Table 1. This is due to the fact that the counterfactual treatment period are the summer months June through August, when mobility is substantially higher compared to other times of the year.

significant reduction in the number of road trips. Between June and August 2022, the number of people traveling on the road decreased by an average of 36 trips, or 5%. This finding suggests only modest switching from car to train usage in response to the ticket. Overall, it seems that the 9-Euro Ticket primarily encouraged people to travel more rather than prompting substantial shifts in transportation mode.

Figures 1a and 1b show the results of the event-study analysis. The first solid vertical line marks the week of the introduction of the 9-Euro Ticket, while the second vertical line marks the week of its expiration. We estimate an almost constant increase in the number of train trips during the treatment period (cf. Figure 1a). In nearly every week from June to August 2022, the number of train trips between any two locations was between 35-40% higher than it would have been without the 9-Euro Ticket. By the end of the treatment period, the excess number of train trips revers back to close to zero. Overall, the pattern confirms the parallel trends assumption, with very flat and insignificant pre- and post-treatment period trends.

With regards to the number of road trips, we observe a gradual decline throughout the treatment period rather than a sudden drop (see Figure 1b). Overall, however, the reduction in car trips is rather limited, and does not reach conventional levels of significance in most weeks.

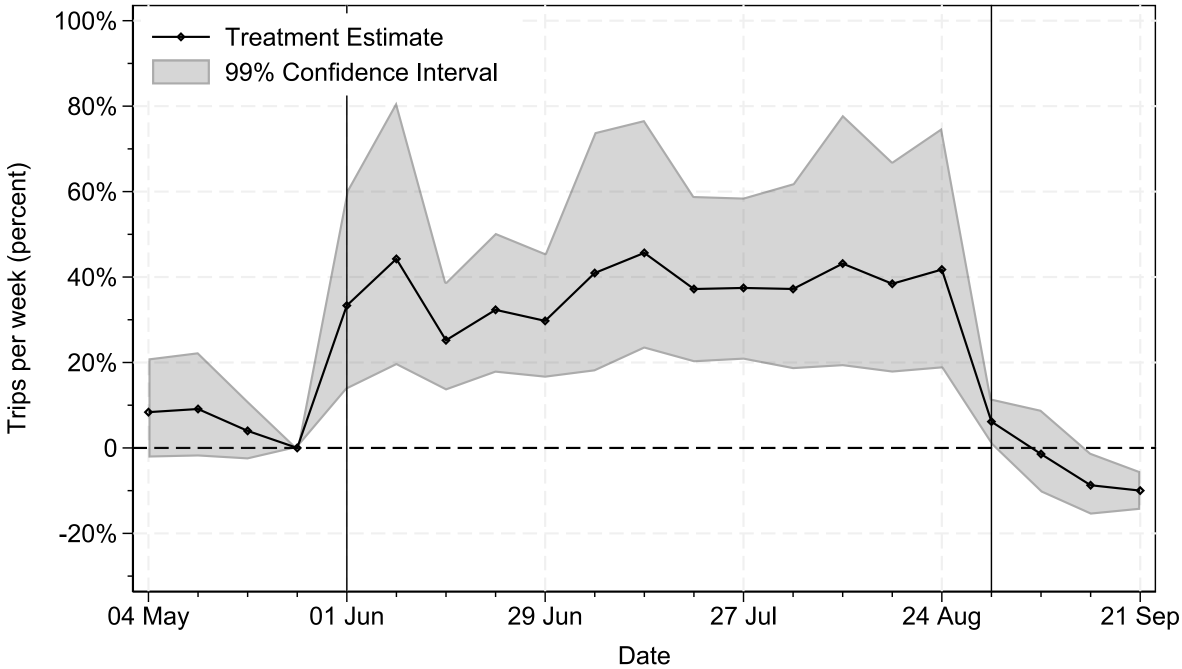
5.2 Robustness Checks and Heterogeneity Analysis

In this section, we examine the heterogeneity of the estimated treatment effect using the mobile network-based mobility data. We begin by examining whether the impact of the 9-Euro Ticket on train and car traffic varies across space and time. We specifically assess whether our treatment effect estimate varies based on the distance between the origin and destination county of a trip (i.e., (i) below 100 km, (ii) between 100 and 200 km, (iii) between 200 and 300 km, (iv) above 300 km)[7] and time of the day ((i) commuting time/weekdays between 6-9am and 4-6pm, (ii) weekdays between 9am-4pm and 6pm-6am, (iii) weekends and holidays). In addition, we explore whether the effect of the 9-Euro Ticket varies across (i) urban touristic destinations, (ii) rural touristic destinations, and (iii) non-touristic destinations.[8] Finally, we

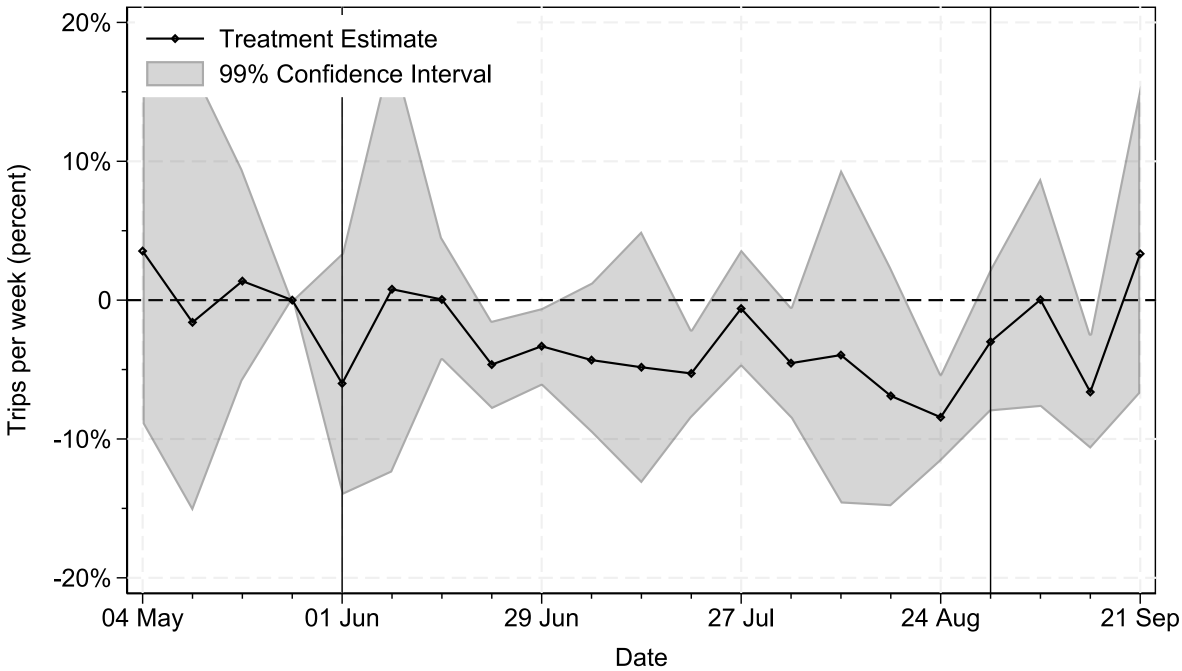
[7]We use the Euclidean distance between the origin and destination counties' centroids as a proxy for the travel distance since our data does not include information about the distance of single trips.

[8]Categories (i) and (ii) include both trips that end and those that start in a rural/urban touristic county in order to account also for people's return journeys. The classification of urban and rural counties is taken from the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (*Bundesinstitut für Bau-, Stadt- und Raumforschung*). Touristic counties are identified based on the number of guests in accommodation facilities in May 2022. We define the top ten touristic counties with respect to the number of guests in accommodation facilities in May 2022 as regions with high tourism activity. These regions account for almost one-third of the total German guest arrivals in May 2022.

Figure 1: Results from Event-Study Analysis – Mobile Network-based Mobility Data



(a) Train 2022 vs. 2019



(b) Road 2022 vs. 2019

Notes: The figures show the estimated event-study coefficients from Equation 3, whereas the coefficient estimates have been transformed into percentage changes following the approach explained in Section 4.3. The top figure shows the effect of the 9EUR ticket on the number of train trips, the bottom figure on the number of road trips. The shaded areas represent 99% confidence intervals.

test whether the effect is different in metropolitan areas. For all these heterogeneity analyses, we re-estimate Equation 1 based on subsamples that include only observations fulfilling the respective criterion. That is, we re-estimate Equation 1 only for county-pairs that are not more than 100 km (or between 100-200 km / 200-300 km / more than 300 km) apart, for trips that took place on weekdays between 6–9am or 4–6pm (on weekdays between 9am–4pm and 6pm–6am/on weekends and holidays), and so forth.

Figure 2 illustrates the estimated heterogeneous treatment effects along with 99% confidence intervals. The results for train trips are presented in the left panel. For comparison, the first row of Figure 2 shows the treatment effect estimate from our baseline specification, as presented in Table 4.

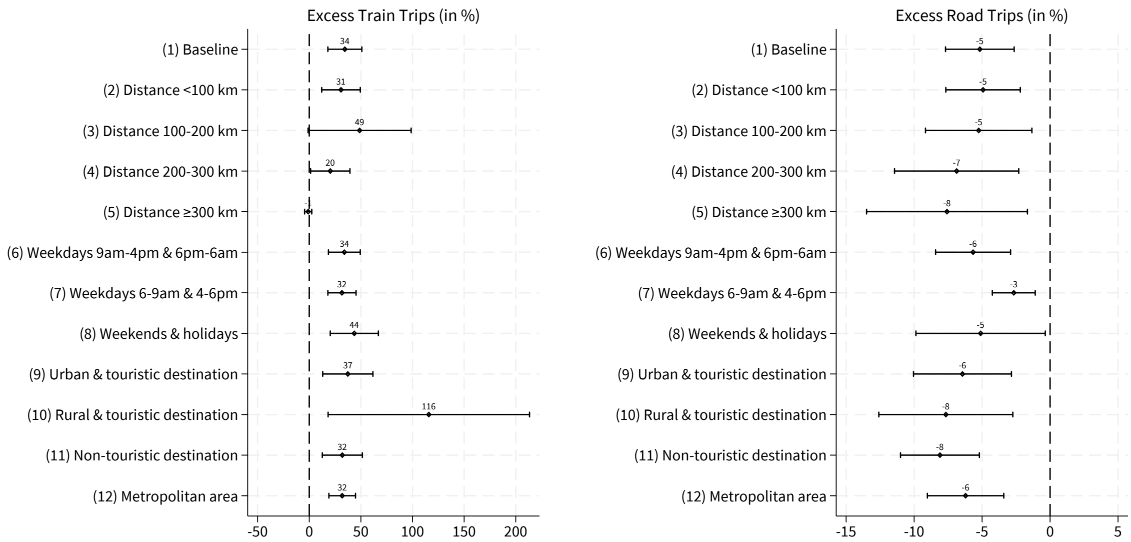
Rows (2) to (5) of Figure 2 show the results for different distances between the origin and destination county of a train trip. Our findings reveal that the effect of the 9-Euro Ticket on the number of train trips tends to decrease with travel distance. While the number of short-distance (below 100 km) and medium-distance (between 100-200 km) train travels per week increased by an average of 31% and 49%, respectively, during the treatment period, the number of long-distance trips (more than 300 km) remained roughly unchanged. This result aligns with expectations, because the 9-Euro Ticket was applicable only to local and regional trains, which typically operate shorter distances. While it is possible to travel across the whole of Germany using only regional trains, the extended travel duration and potential need for multiple transfers make it less appealing compared to long-distance Intercity Express (ICE) trains.[9]

Rows (6) to (8) of Figure 2 show treatment effect estimates for different times. We observe a larger increase in train trips outside typical commuting times, with an average of 34% more trips on weekdays between 9 am and 4 pm and 4 pm to 6 pm, and a 44% increase on weekends and holidays. However, there is also a sizable additional train traffic during commuting times, with a 32% increase. This suggests that people utilized the 9-Euro Ticket primarily for leisure travel, but also for their trips to work.

The treatment effect estimates for different destinations, presented in rows (9) to (11), further support the conclusion that the 9-Euro Ticket was predominantly utilized for leisure activities. The increase in the number of train rides to touristic destinations is significantly higher

[9]For instance, traveling from Berlin to Hamburg, which are roughly 300 km apart, takes around four hours by regional train, whereas an ICE train covers the same distance in just under two hours. A trip from Berlin to Munich, which are around 600 km apart, takes around four hours by ICE and almost ten hours with regional trains.

Figure 2: Heterogeneity Analysis – Mobile Network-based Mobility Data



Notes: The figures show the estimated coefficients of the 9-Euro Ticket dummy from difference-in-difference estimation (cf. Equation 1) The coefficients have been transformed into percentage changes following the approach explained in Section 4.3. The left figure shows the results for the number of train trips, the right figure for the number of road trips. Row (1) shows the results from the baseline specification and the remaining rows represent modifications. All specifications include the full set of control variables, but their coefficients are omitted to save space. The whiskers represent 99% confidence intervals.

compared to non-touristic destinations. Interestingly, we find a remarkably large increase in train trips to rural touristic counties (+116%), whereas the effect on urban touristic (+37%) and non-touristic destinations (+32%) is notably smaller and roughly of same size. Hence, it appears that rural touristic destinations in Germany particularly benefited from the 9-Euro Ticket. Finally, the treatment effect estimate for metropolitan areas is roughly equal to our baseline effect (row (12)).

The right panel of Figure 2 presents the results for road trips. By and large, we observe a somewhat similar decline in the number of road trips with respect to the travel distance. Consistent with our results for train trips, we find the smallest decrease in the number of road trips on weekdays during typical peak-commuting hours (−3%; row (7)). However, in comparison to the observed pronounced increase in the number of train trips, the estimates for road trips are of modest size, indicating yet again that a considerable fraction of people used the 9-Euro Ticket for journeys they would otherwise not have undertaken. With regard to the results for different travel destinations (rows (9)–(11)) and metropolitan areas (row (12), we find no pronounced differences.

6 Results from Traffic Volume Data

6.1 Baseline Results

Next, we turn to the results for our traffic volume data from the road monitoring stations. Table 5 presents the estimates from the DiD estimation (cf. Equation 2), with the weekly number of passenger cars as the outcome variable. We find only a minor effect of the 9-Euro Ticket on traffic volume. Between June and August 2022, the average number of passenger cars decreased significantly by 5,111 per monitoring station per week. This corresponds to a relative decrease of about 1.4%.

Figure 3 illustrates the event-study estimates obtained from equation (4), which are transformed into percentage changes based on equation 6. Two things are notable when looking at the figure. First, the coefficients for the weeks prior to the introduction of the 9-Euro Ticket are quantitatively small and statistically insignificant. This corroborates that, in the weeks leading up to the introduction, traffic volume in Germany followed a similar trajectory in 2022 as it did in 2019, supporting the parallel trends assumption. Second, with the introduction of the 9-Euro Ticket, the number of passenger vehicles starts to decrease significantly. We find the largest reduction in traffic volume in the first weeks of the treatment period. However, over the course of the treatment period, the effect diminishes again. Overall, our event-study results support the conclusion that the 9-Euro Ticket encouraged only a very modest substitution of cars for other modes of transport.

6.2 Robustness Checks and Heterogeneity Analysis

We now turn to the heterogeneity analysis of traffic volumes. Specifically, we examine whether the estimated reduction in traffic volume was more pronounced on weekdays, during typical commuting hours, or at certain types of measurement stations. For the heterogeneity analysis, we re-estimate Equation 2 based on the respective heterogeneity criterion.

The first row of Figure 4 shows the treatment effect estimate from our baseline specification, as presented in Table 5, for comparison (traffic volume reduction of ca. -1.4%). Rows (2) and (3) examine whether the effect varies with the type of measurement station. The Federal Highway Research Institute (BASt), which collects the traffic volume data, provides a typology

Table 5: Results from DiD Estimation: Traffic Volume

	Traffic Volume
Treatment effect (number of cars)	-5111.090
	[-7458.816,-2763.365]
Number of public holidays	2450.542
	[-2321.183,7222.268]
Number of school vacation days	-1910.904
	[-2228.374,-1593.434]
School vacation (impulse dummy)	5203.584
	[4169.039,6238.128]
Summer vacation (impulse dummy)	678.668
	[-211.267,1568.604]
Rainfall	-59.280
	[-92.075,-26.485]
Temperature	-836.141
	[-1383.608,-288.674]
September 2022 dummy	331.943
	[-2280.663,2944.549]
Treatment effect (in %)	-1.365
Counterfactual	374424.957
Observations	51,198

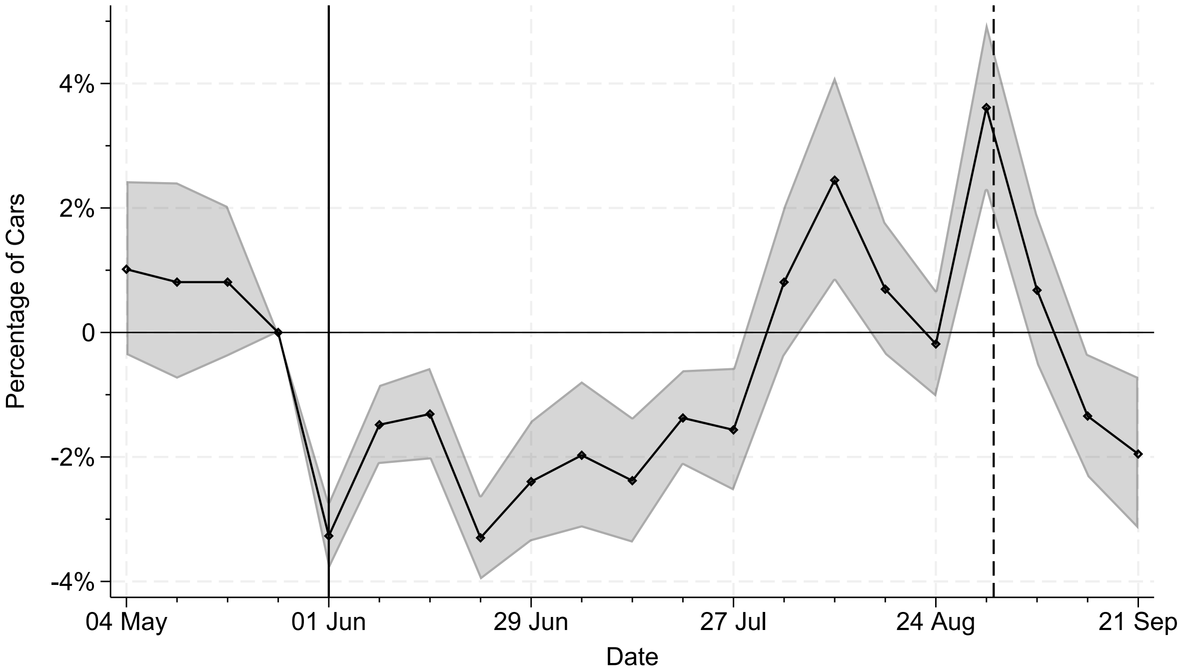
Notes: The table shows the results from difference-in-difference estimation (Equation 2). 99% confidence intervals in brackets. The row 'counterfactual' shows the predicted average weekly number of passenger cars per monitoring station if the 9-Euro Ticket was not introduced (see Section 4.3 for details).

of its stations. They differentiate between stations with a larger share of leisure and holiday traffic, and those which are predominantly frequented by commuter traffic (for more details see Fitschen and Nordmann (2017)). We observe a smaller reduction in traffic volume at commuter stations compared to those recording mostly leisure traffic (-1% vs. -5%). This suggests that leisure trips by car were more likely to be substituted for train travel than commuter trips.[10]

Rows (4) to (6) show estimates for different times of the week. We differentiate between off-peak commuting hours (row (4)), peak commuting hours (row (5)), and weekends/holidays (row (6)). We observe a larger reduction in traffic volume (about -3%) on weekends and holidays, when leisure trips are more likely. In contrast, we do not find a larger reduction in traffic volume during peak commuting hours compared to other hours during the weekdays. In row (7) we restrict our analysis to traffic monitoring stations located in metropolitan areas (e.g. at urban highways). These stations are likely to record a larger share of short-distance travel, for which the 9-Euro Ticket should have generated stronger substitution effects (since it was

[10]Please note that our heterogeneity analysis in Figure 4 uses sometimes different heterogeneity criterion than in Figure 2 (based on the mobile network-based mobility data). This is due to the fact that the mobility data records also distances travelled as well as mobility flows between counties. In contrast, the data from the traffic monitoring stations allows for other heterogeneity checks, such as the type of the station.

Figure 3: Results from Event-Study Analysis – Traffic Volume Data



Notes: The figure shows the event-study coefficients estimated from equation (4), 2022 vs 2019, transformed into percentage changes based on equation 6. It displays 99 percent confidence intervals, with standard errors clustered at the station level.

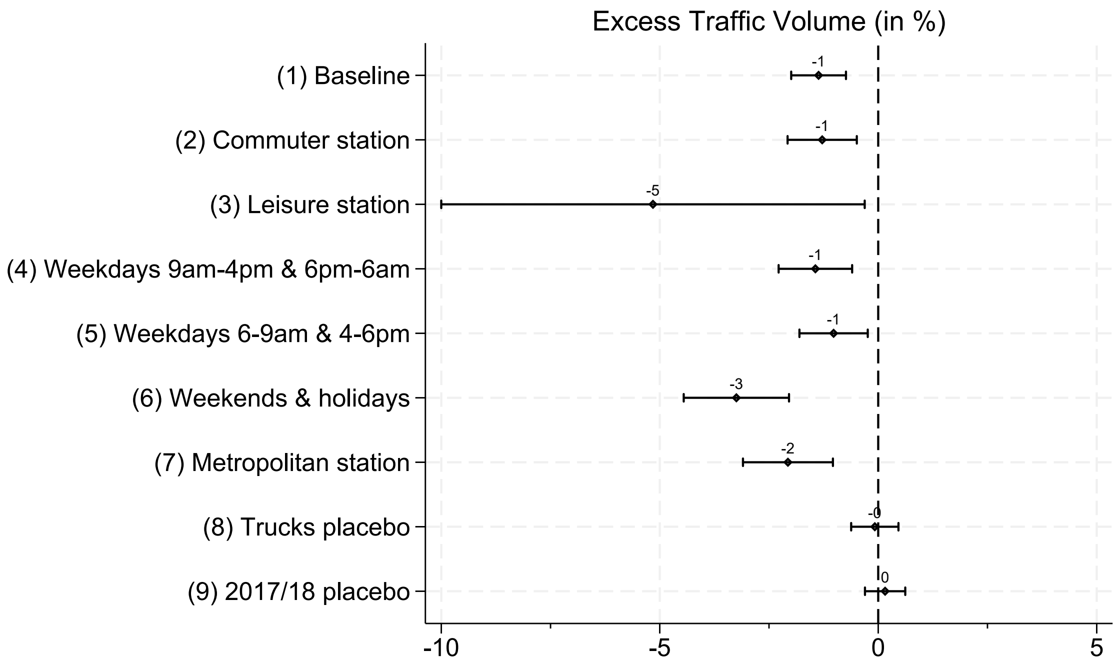
only valid for local and regional public transport).[11] Although we do find a larger reduction in traffic at metropolitan monitoring stations compared to our baseline estimate, the effect size remains modest (around -2%).

Finally, we execute two placebo tests. First, we replicate our analysis using the number of recorded trucks instead of passenger vehicles as outcome variable. The number of trucks should be unaffected by the introduction of the 9-Euro Ticket. Indeed, we estimate zero reduction in truck traffic during the time period of the 9-Euro Ticket (row (8)). Second, we re-run our analysis on traffic volume data from 2017/2018 vs 2019, using 1st of June 2019 as the placebo event date (row (9)).[12] We do not find any evidence of a reduction in the number of passenger vehicles from June to August 2019. This suggests that our results from June to August 2022 are not driven by traffic volume reductions which occur regularly at this time of the year. Taken together, our results above corroborate our findings from the mobile network-based mobility data. Reduction in car traffic is very modest and appears to be (at least partly) driven by the

[11] Note that our traffic volume data does not record the length of a drive.

[12] Please note that the traffic volume data is the only non-proprietary data we use. Thus, it allows us to use also previous years as a placebo.

Figure 4: Heterogeneity Analysis – Traffic Volume Data



Notes: The figure shows the estimated coefficients of the 9-Euro Ticket dummy on traffic volume from difference-in-difference estimation (cf. Equation 2). The coefficients have been transformed into percentage changes following the approach explained in Section 4.3. Row (1) shows the results from the baseline specification and the remaining rows represent modifications. All specifications include the full set of control variables, but their coefficients are omitted to save space. The whiskers represent 99% confidence intervals.

substitution of leisure trips from cars to trains. In contrast, commuting trips by passenger vehicles seem to be more difficult to be substituted for train travel.

7 Results from Train Delay Data

7.1 Baseline Results

Table 6 presents the DiD results using data on train delays and thus, aims to measure adverse effects of the 9-Euro Ticket on infrastructure and train network quality. Column (1) presents results for all trains, whereas column (2) and (3) differentiate between regional and long-distance trains. For all trains, we find a significant increase in delayed trains of ca. 4 percentage points. Given that we find around 14 percent of all trains to be delayed for the counterfactual, this means an increase in delays of 30%. For regional trains (column 2), we find the treatment effect to be even stronger, with around 41%. That is, under the counterfactual of no treatment,

Table 6: **DiD estimation: share of delayed trains (≥ 6 min.)**

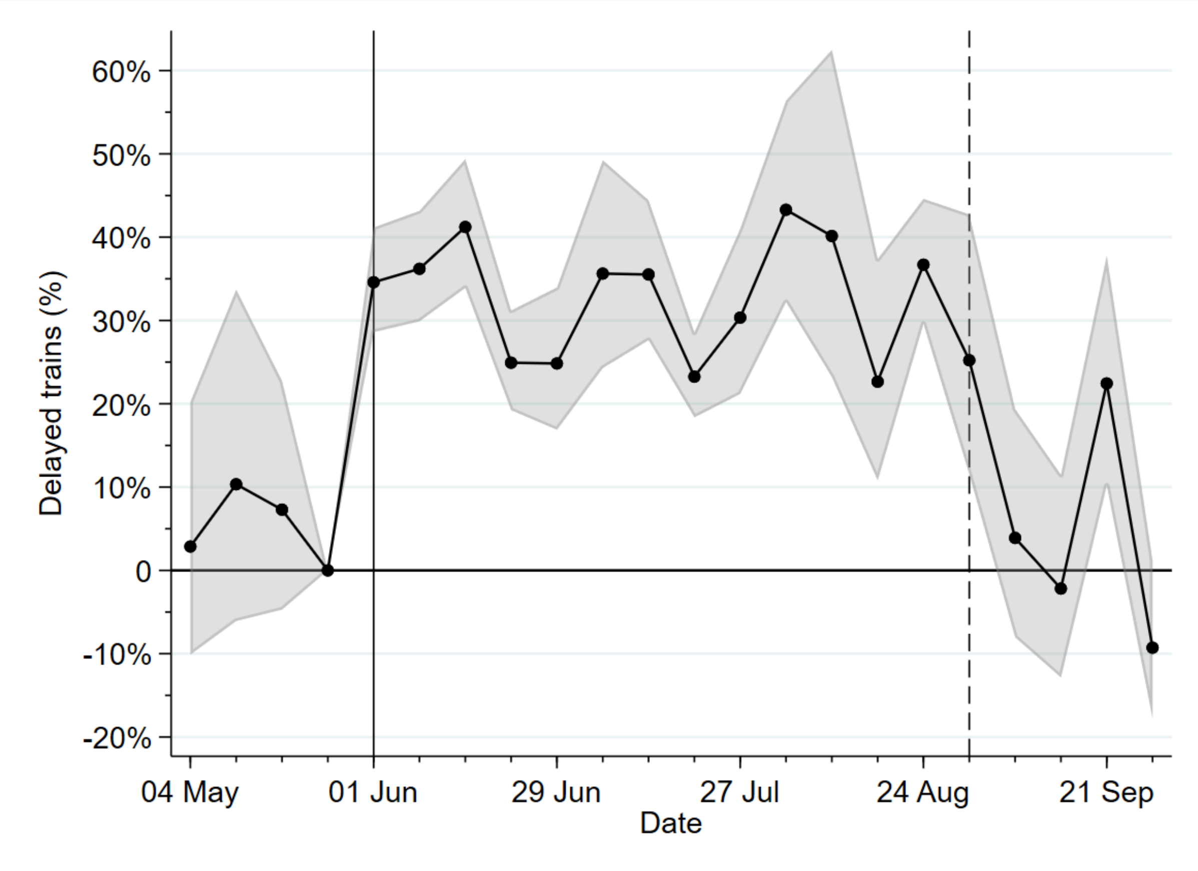
	(1) All trains Share delayed	(2) Regional trains Share delayed	(3) Long-dist. trains Share delayed
Treatment effect (share of delayed trains)	0.0423	0.0373	0.0495
	[0.032,0.053]	[0.025,0.049]	[0.015,0.084]
Precipitation	0.0000343	0.0000999	-0.000153
	[-0.00024,0.00031]	[-0.00023,0.00043]	[-0.00070,0.00039]
Temperature	0.00416	0.00399	0.00669
	[0.0023,0.0060]	[0.0021,0.0059]	[0.0023,0.011]
Nr of trains	-0.0000689	0.000177	0.0000384
	[-0.00017,0.000034]	[0.000062,0.00029]	[-0.00012,0.00019]
Number of public holidays	-0.00000278	0.0000354	0.0000435
	[-0.000038,0.000033]	[-0.000035,0.00011]	[-0.000081,0.00017]
School vacation (impulse dummy)	-0.00766	0.00540	0.0101
	[-0.035,0.019]	[-0.035,0.046]	[-0.054,0.075]
Summer vacation (impulse dummy)	0.0124	0.0120	-0.0222
	[-0.020,0.044]	[-0.031,0.055]	[-0.098,0.054]
Number of school vacation days	-0.000000465	-0.000000318	-5.49e-08
	[-0.0000048,0.0000039]	[-0.0000082,0.0000076]	[-0.000016,0.000016]
September 2022 dummy	0.0107	0.0230	0.0111
	[-0.0072,0.029]	[0.0018,0.044]	[-0.028,0.050]
Treatment effect (in %)	29.90	41.09	18.30
Counterfactual	0.14	0.091	0.270
Observations	125,488	119,125	25,957

Notes: The table shows the results from difference-in-difference estimation (Equation 2). 99% confidence intervals in brackets. The row 'counterfactual' shows the predicted average weekly share of delayed trains per station if the 9-Euro Ticket was not introduced (see Section 4.3 for details).

9.1% of the regional trains would have been delayed, while the introduction of the 9-Euro Ticket elevated this share by 3.73 percentage points. Regarding long-distance trains (column 3), we find a treatment effect of 18%. Under the counterfactual of no treatment, 27% of the long-distance trains would have been delayed, whereas the presence of the 9-Euro Ticket lifted this share by another 5.95 percentage points. Overall, the evidence suggests that the 9-Euro Ticket decreased infrastructure quality through a significant increase in train delays. Not only directly treated regional trains were adversely affected by the the 9-Euro Ticket but also long-distance trains, potentially through intensified network congestion.

Figure 5 presents the results of the event-study model introduced in Equation 4. It shows that the share of delayed trains (regional and long-distance) increased significantly in response to the 9-Euro Ticket. Moreover, we observe mostly flat and insignificant pre- and post-treatment period trends, indicating that the observed deterioration in delays indeed was caused by the 9-Euro Ticket.

Figure 5: Results from Event-Study Analysis – Train Delay Data

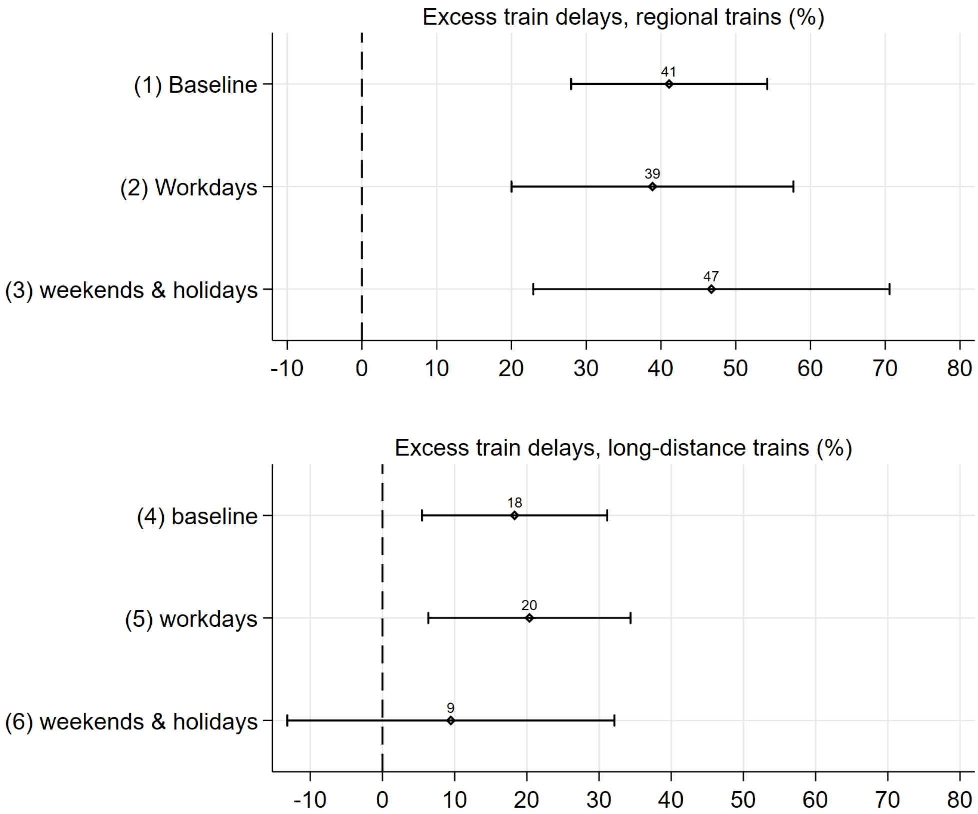


Notes: The figure shows the event-study coefficients estimated from Equation 6, comparing the share of delayed trains in 2022 with 2019, transformed into percentage changes based on equation 6. It displays 99 percent confidence intervals, with standard errors clustered by station-year and week.

7.2 Robustness Checks and Heterogeneity Analysis

Figure 6 presents heterogeneity estimates of modified versions of Equation 2, distinguishing between regional trains (upper panel) and long-distance trains (lower panel). Row (1) of each panel presents the baseline estimates from our did estimation. In rows (2) and (3), we differentiate between workdays and weekends/holidays. For regional trains, the treatment effect is more pronounced during weekends and holidays, although the confidence interval largely overlaps with that for workdays. This observation suggests a greater utilization of the 9-Euro Ticket for leisure activities, corroborating the findings from the mobile network-based mobility data as well as traffic volume data. Regarding long-distance trains, the situation seems different. The 9-Euro Ticket resulted in stronger delays for long-distance trains during weekdays (row (5)), whereas during weekends and holidays (row (6)), the point estimate is

Figure 6: Heterogeneity Analysis – Train Delay Data



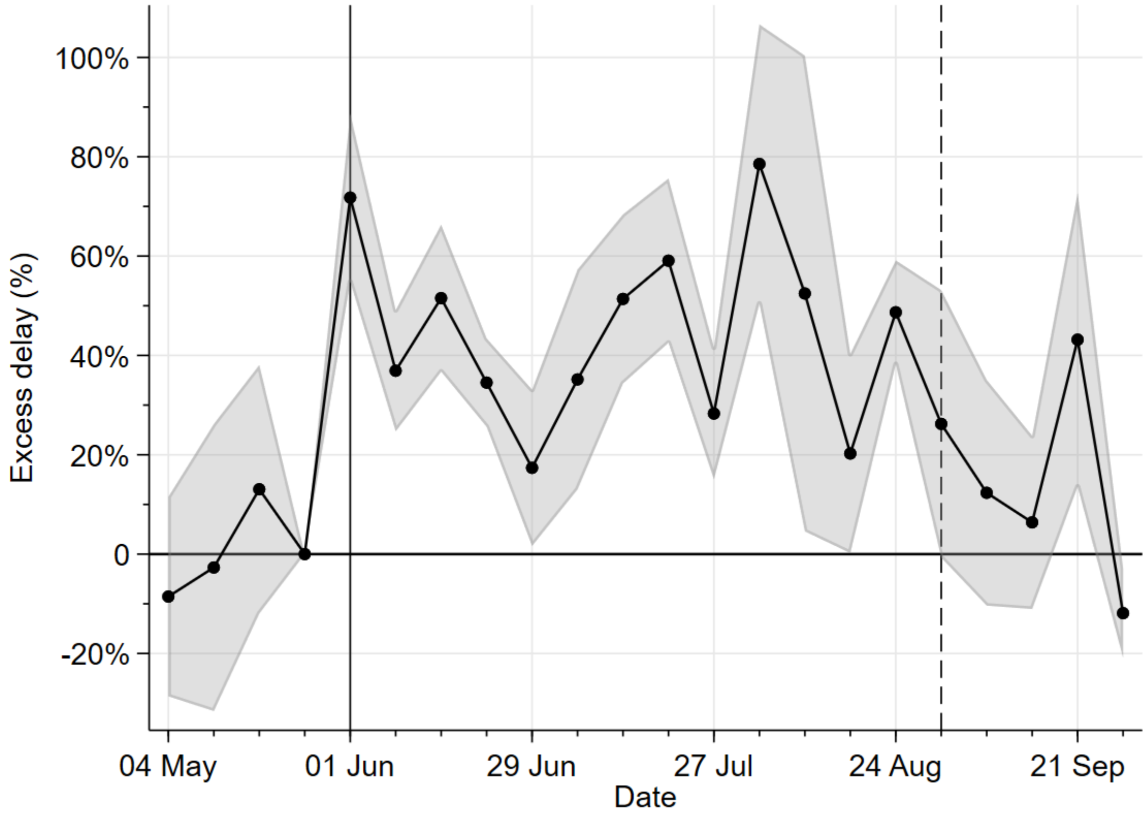
Notes: The figures show the estimated coefficients of the 9-Euro Ticket dummy on the share of train delays (≥ 6 min.) from difference-in-difference estimation (cf. Equation 2). The coefficients have been transformed into percentage changes following the approach explained in Section 4.3. Rows (1) and (4) show the results from the baseline specifications for regional and long-distance trains, respectively. The remaining rows represent modifications. All specifications include the full set of control variables, but their coefficients are omitted to save space. The whiskers represent 99% confidence intervals.

smaller and statistically insignificant.[13]

So far, the analysis of train delays has concentrated on the extensive margin, examining the increase in the share of delayed trains. We can also assess the intensive margin by investigating the number of minutes of the train delay. Figure 7 presents event-study results, showing that delays of regional trains intensified in response to the introduction of the 9-Euro Ticket, with the effect diminishing at the end of the treatment period. The average treatment effect indicates a substantial 44% increase in the severity of train delays, demonstrating its economic significance.

[13]Please note that our heterogeneity analysis in Figure 6 is less encompassing than for the other two datasets since we do not have hourly or county information in this data, which inhibits some of the analyses.

Figure 7: Intensive margin: excess train delays in minutes (transposed into percentage changes)



Notes: The figure shows the event-study coefficients estimated from equation (4), 2022 vs 2019, transformed into percentage changes based on equation 6. In contrast to the extensive-margin estimates presented in Figure 5, this figure shows the estimates of a model where the dependent variable is the train delay in minutes. The coefficient estimates are transposed into percentage changes. 99 percent confidence intervals are displayed, with standard errors clustered clustered by station-year and week.

8 Potential Threats to Identification

8.1 Introduction of a Fuel Tax Break

A potentially confounding factor to our identification strategy might be the introduction of the so-called "Tankrabatt". This "Tankrabatt" was a temporary reduction of the tax on fuels, which lasted for the same time period as the 9-Euro Ticket. Specifically, the decrease in fuel prices due to the tax break means that there was an economic incentive to drive more compared to the time period before the 9-Euro Ticket was implemented. Thus, our estimates regarding the decreased number of car trips in response to the 9-Euro Ticket could be larger (i.e. more negative) if the fuel tax cut would have not been in place. In the following, we will evaluate the potential impact this tax rebate may have on our findings.

The fuel tax break amounted to 29.55 cents per liter for gasoline and 14.04 cents per liter for diesel. Evidence suggests that the rebate was largely passed through to end-consumer prices (Fuest et al., 2022; Dovern et al., 2023; Schmerer and Hansen, 2023; Seiler and Stöckmann, 2023). Indeed, the average fuel prices were slightly lower during the months of the fuel tax break, as shown in Appendix Figure A.1. Thus, this tax rebate could have potentially affected mode choice and mobility patterns. However, the overall price reduction due to the tax break appears to be modest (around 10%) compared to the substantial fare reduction of the 9-Euro Ticket.

To get a better sense of how much the "Tankrabatt" might have potentially confounded our findings, we assess the impact of lower fuel prices on our estimates. Therefore, we need to gauge how responsive mobility patterns are to possible fuel price changes. Previous literature suggests that in Germany, the fuel price elasticity of kilometers traveled is about -0.4 (Alberini et al., 2022; Frondel and Vance, 2018). These estimates consider that people react in several ways to fuel price changes. For instance, they comprise behavioral responses such as buying a less fuel efficient car, which seem unlikely in the context of a short-term fuel tax break. Frondel et al. (2021) estimate an elasticity of -0.2 for the number of car trips a household takes in a week, which seems to be a more relevant response margin in our setting.

In the following, we calculate the counterfactual change in the number of car trips in response to the 9-Euro Ticket if the "Tankrabatt" would not have been in place ($\Delta y_{\text{no tr}}$). We employ estimates of the fuel price elasticity (e), the observed change in the number of car trips ($\Delta y_{\text{with tr}}$), as well as fuel prices with the "Tankrabatt" ($p_{\text{with tr}}$), and the hypothetical fuel prices without the "Tankrabatt" ($p_{\text{no tr}}$):

$$\Delta y_{\text{no tr}} = \Delta y_{\text{with tr}} \cdot [1 + (1 - \frac{p_{\text{with tr}}}{p_{\text{no tr}}}) \cdot e] \tag{7}$$

We use the elasticity estimate from Frondel et al. (2021) of $e = -0.2$, as it closely aligns with our main outcome variables related to traffic volume and the number of road trips. Moreover, we adopt a conservative approach and assume the incidence was fully passed on to drivers. The average fuel price during the treatment period ($p_{\text{with tr}}$) was 1.84 Euro/l.[14] Adding back the tax break to the observed fuel price under the assumption of full pass-through gives us a hypothetical price $p_{\text{no tr}}$ of 2.08 Euro/l during the treatment period.

[14]We weight diesel and gasoline prices based on the ratio of registered passenger vehicles. In Germany, 31% of all registered passenger vehicles are diesel and 64% are gasoline (Kraftfahrt-Bundesamt, 2023).

Table 7: Counterfactual excluding 'Tankrabatt'

	Car use (elasticity)				Train use (cross elasticity)	
	Mobile network mobility data		Traffic volume data		Mobile network mobility data	
	Level	Percent	Level	Percent	Level	Percent
Main estimate	-36.006	-5.124	-5111.090	-1.365	122.461	34.465
Corrected estimate	-36.864	-5.246	-5233.664	-1.397	123.899	35.870
Change in %	-2.4	-2.4	-2.4	-2.4	1.2	1.2

Notes: The table shows the results from Tables 4 and 5 corrected by the possible price effect of the 'Tankrabatt'.

We use our baseline estimates of the change in car trips and traffic volume as $\Delta y_{\text{with tr}}$ (see Table 4 and 5, respectively). For instance, based on the mobile network-based mobility data we estimated that the 9-Euro Ticket lead to an average decline of 36 car trips between any two counties (or -5.1%), see Table 4. Solving for $\Delta y_{\text{no tr}}$, we find that the average reduction in car trips would have been ca. 37, or 2.4% larger without the fuel tax rebate (see rows (1-2) of Table 7). For traffic volume we estimate similar modest changes if the fuel tax break would not have been in place (see rows (3-4) of Table 7). In sum, we conclude that the confounding effect of the tax break is rather limited and does not qualitatively change the conclusions drawn from our baseline estimates.

We also examine the cross fuel price elasticity on the number of train trips for Germany, using equation 7. Related to our reasoning above, our estimate on the increased number of train trips in response to the ticket could be larger (i.e. more positive) if the fuel tax cut would have not been in place. Following Waluga (2017), we assume that the cross price elasticity is 0.1. Moreover, we use the number of train trips estimated in Table 4. As shown in Table 7, the hypothetical number of train trips without the fuel tax break would have been 1.2% higher.

8.2 Potential Anticipation Effects

People may have factored the forthcoming subsidized ticket into their future travel plans, postponing planned trips while awaiting the implementation of the ticket. However, in our event study estimates we do not observe considerable trends in the upcoming weeks prior to the start of the 9-Euro Ticket. Furthermore, the resolution to introduce the ticket passed the German Bundestag on May 19 2022, only 12 days before the ticket became valid. This short time period speaks against large postponements of already planned travel trips.

9 Conclusion

The 9-Euro Ticket, an almost fare-free public transport ticket, was introduced in Germany in 2022. The political intention was to cushion rising living costs in the aftermath of the Russian invasion in Ukraine and to encourage people to switch to more environmentally friendly modes of transportation. However, the impact of the ticket on mobility patterns and the use of public transport has not yet been thoroughly studied.

In this study, we examine whether this 9-Euro Ticket indeed led to a change in mobility patterns towards greater use of public transport, as well as a reduction in car traffic. We use different datasets to estimate the potential effects of the 9-Euro Ticket, including road and train mobility data from mobile network devices (e.g., cellphones, tables, smartwatches) as well as car traffic volume data from road monitoring stations. We compare outcomes between 2022 and 2019 using event-study and difference-in-differences designs. Our main findings are that the 9-Euro Ticket led to a substantial increase in train trips, but only to a very modest reduction in car traffic. Our findings suggest that the 9-Euro Ticket primarily encouraged people to travel more, mainly for leisure-related purposes, rather than inducing significant substitutions away from car mobility.

Furthermore, we investigate adverse effects on infrastructure quality. We find a substantial increase in train delays in response to the 9-Euro Ticket, which places an additional burden on the already heavily delayed rail infrastructure in Germany. Our estimates suggest that not only regional trains, which were directly covered by the 9-Euro Ticket, experienced significant delays, but even long-distance trains. Thus, there is suggestive evidence that the entire train network suffered from the large influx of additional passengers.

As the 9-Euro Ticket was only implemented as a measure from June to August 2022, we mostly investigate short-term behavioral responses. Long-term changes in mobility patterns, such as potential shifts away from car ownership, are likely to be influenced only by more prolonged policy measures. Another limitation of our study is that our data does not fully capture urban road traffic. Our mobile network-based mobility data covers trips of at least 30 kilometers, and the traffic volume data measures traffic at road monitoring stations which are primarily located on freeways and highways. Therefore, our study leaves room for future research on the effects of the 9-Euro Ticket on mobility substitutions within urban areas. Moreover, we abstained from making efficiency statements as in Andor et al. (2023), although our results indicate a similar direction. Additionally, we did not speculate about potential effects on social cohesion and participation, which could arise if the measure was extended and allowed poorer people to travel more. In sum, however, our study calls for some caution regarding potential mode substitution and infrastructure quality when implementing such (almost) fare-free 'go-anywhere' tickets for public transport.

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Appendix

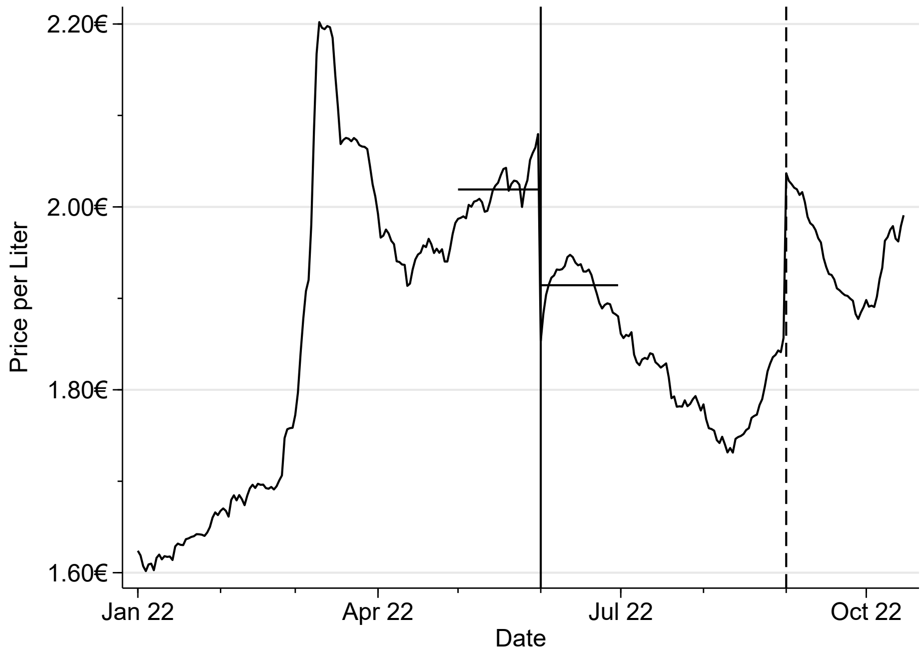

Figure A.1: Fuel prices in Germany in 2022

Notes: The figure shows a weighted average of daily fuel prices in Germany from January to October 2022. Diesel and gasoline prices are weighted based on the ratio of registered passenger vehicles in 2022 (In Germany, 31% of all registered passenger vehicles are diesel and 64% are gasoline (Kraftfahrt-Bundesamt, 2023)).The solid vertical (dashed) line represents the introduction (expiration) of the fuel tax break. The horizontal lines display the monthly average fuel price for May and June, respectively.

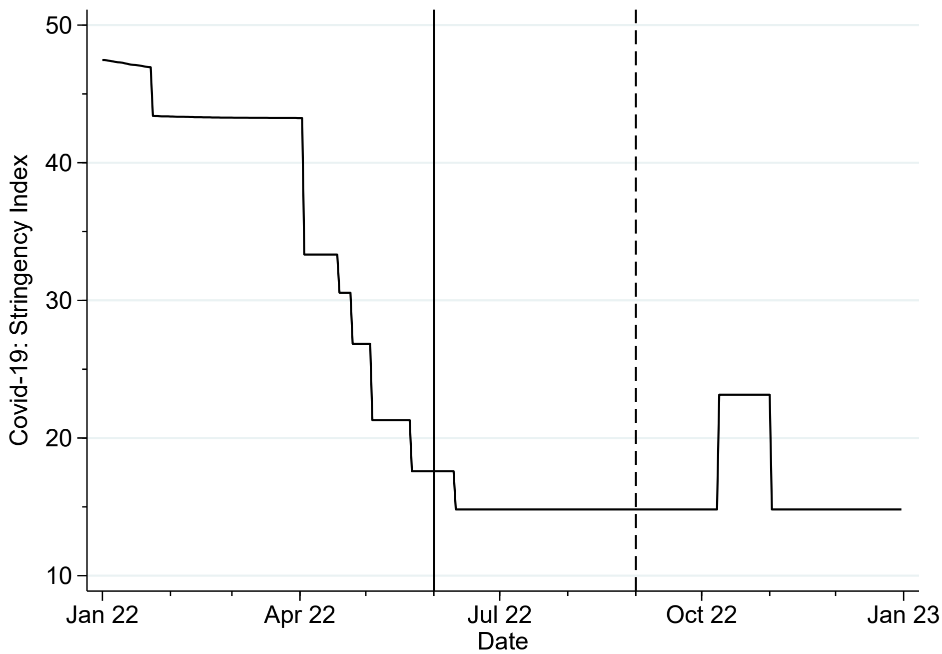

Figure A.2: Covid-19 restrictions: stringency index for Germany

Notes: The figure shows the Covid-19 stringency index for Germany (based on Hale et al., 2021). The solid vertical (dashed) line represents the introduction (expiration) of the 9-Euro Ticket. The figures shows that COVID-19 restrictions remained basically constant throughout the time period of the ticket.

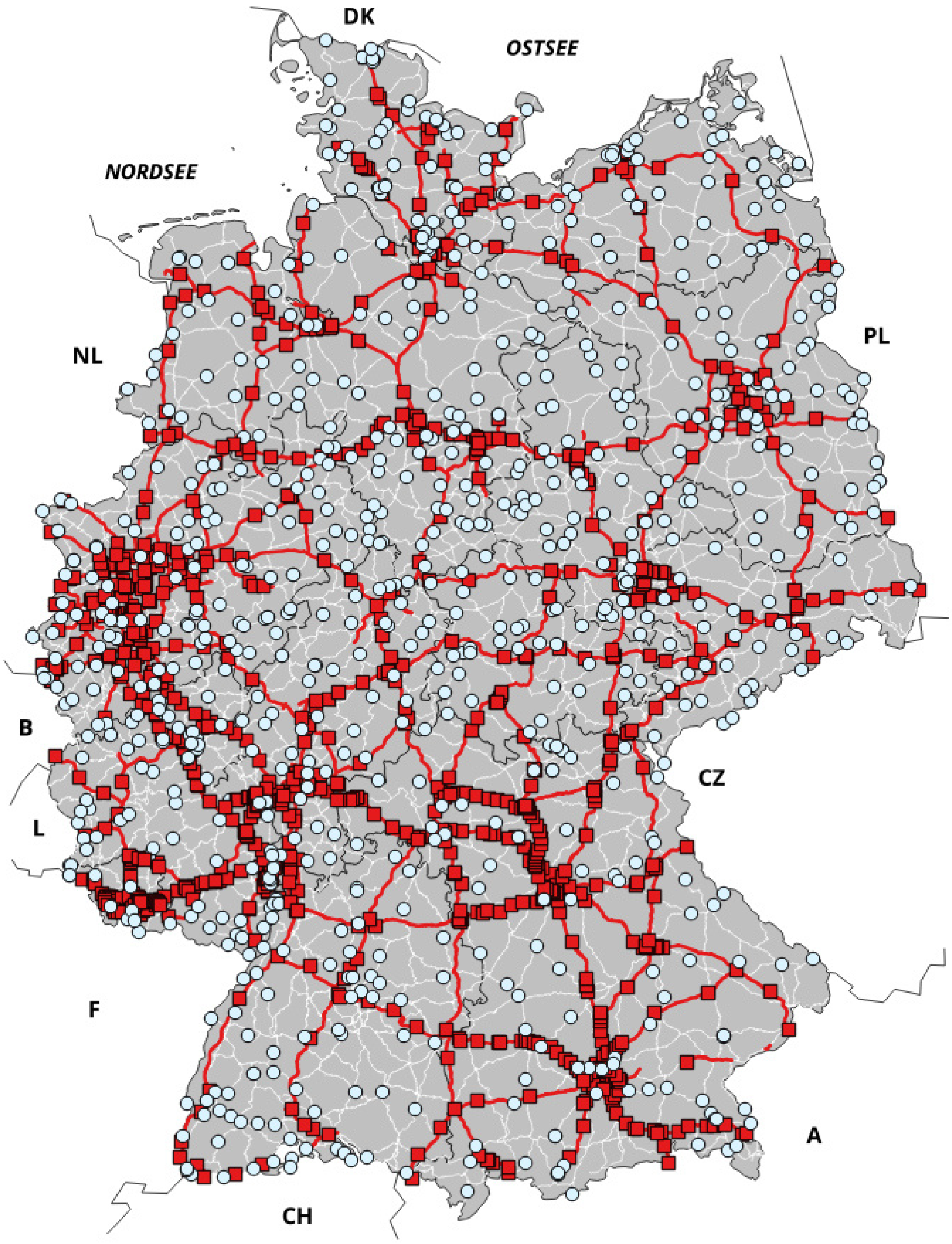

Figure A.3: Traffic volume monitoring stations in Germany

Notes: The figure shows a map of all traffic volume monitoring stations run by the Federal Highway Research Institute (BASt, 2022). Red squares indicate stations on freeways (Autobahnen), whereas white dots indicate stations installed on highways (Bundesstraßen). In total there are 2,095 stations across Germany.