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Ticket to Paradise? The Effect of a Public Transport Subsidy on Air Quality*

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ABSTRACT

This paper provides novel evidence on the impact of public transport subsidies on air pollution. We obtain causal estimates by leveraging a unique policy intervention in Germany that temporarily reduced nationwide prices for regional public transport to a monthly flat rate price of 9 Euros. Using DiD estimation strategies on air pollutant data, we show that this intervention causally reduced a benchmark air pollution index by more than six percent. Our results illustrate that public transport subsidies – especially in the context of spatially constrained cities – offer a viable alternative for policymakers and city planners to improve air quality, which has been shown to crucially affect health outcomes.

Keywords: air pollution, public transport, transport subsidies

JEL Codes: Q53, Q58, R12, R48

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1 Introduction

The UN’s Sustainable Development Goals emphasize the importance of air quality within cities and explicitly list the improvement of urban air quality as a key measure to make agglomerations safer, healthier, more resilient and sustainable.¹ Key contributing factors to air pollution, particularly in cities, are car traffic and congestion. Indeed, research highlights that reduced congestion and traffic can lead to better air quality and better health outcomes (Margaryan, 2021; Knittel et al., 2016; Currie and Walker, 2011). Frequently proposed measures to reduce car traffic and thereby air pollution include the extension of public transport supply and the reduction of its cost, thereby ultimately encouraging a modal switch towards publicly provided means of transportation. This paper leverages a unique policy intervention in Germany to causally estimate how lower public transport prices impact air quality.

In June 2022, Germany introduced the so called “9-Euro-Ticket” (9ET), which temporarily reduced prices for regional public transportation to a flat rate price of 9 Euros per month from June until August. This policy intervention is unusual in the sense that it temporarily and relatively suddenly reduced public transport fares for a whole country. Further, the implied price drop was substantial - in Berlin, for example, the monthly standard fare ticket, normally priced at 86 Euros, experienced a price decrease of about 90%.² The aim of the ticket’s introduction was twofold. First, as part of a set of relief measures, passed in the first half of 2022, mitigating rising cost of living was a central goal of the policy. Second, it was seen as a potential means to promote green mobility by incentivizing a reduction in car traffic and thereby carbon emissions and pollution (Spiegel Online, 2022). The introduction of such a temporary public transport subsidy was highly debated in German politics with parties such as the Greens and the Left supporting an extension of the ticket beyond a three month period, especially if the ticket is proven to successfully incentivize individuals to substitute car travel for public transport (Spiegel Online, 2022).

First descriptive and anecdotal evidence on the 9ET’s impact suggests that car traffic in June 2022 was indeed reduced: following the introduction of the ticket, the level of congestion in many German cities decreased between May and June 2022, while the amount of train travel increased (Süddeutsche Zeitung (SZ), 2022; German Federal Office for Statistics, 2022). A decrease in traffic and congestion in response to the public transport subsidy can also imply positive externalities such as carbon emission reduction and a decrease in air pollution (Beaudoin et al., 2015), which will be the focus of this study. In the absence of effective road pricing systems that may internalize external effects of

¹See Goal 11 at <https://sdgs.un.org/goals>.

²See <https://www.bvg.de/de/tickets-und-tarife/alle-tickets/zeitkarten/monatskarte>.

auto travel such as pollution, interventions in the public transit sector, e.g. subsidies like the 9ET or extending the network, are potential viable second best solutions.

A large body of research shows a positive impact of public transit provision on air quality. Anderson (2014) and Bauernschuster et al. (2017) use unexpected public transport strikes as a quasi-natural experiment and find a temporary increase in congestion and in air pollution respectively. Other papers look at the effect of building or extending new subway lines, which have been shown to positively affect air quality (Chen and Whalley, 2012; Gendron-Carrier et al., 2022). In Germany, Lalive et al. (2018) find a positive effect of railway expansions on air quality. A second strand of literature develops and calibrates quantitative equilibrium models to quantify welfare effects of public transport investments. For instance, Parry and Small (2009) and Basso and Silva (2014) document significant welfare gains from subsidizing public transport. Borck (2019), in a counterfactual analysis, shows that subsidies reduce air pollution, albeit only modestly due to offsetting long term equilibrium effects such as residential relocation. In contrast, causal reduced form evidence on the effect of public transport pricing on air quality is, to the best of our knowledge, scarce and limited to the study of price increases. Yang and Tang (2018) using a synthetic control group approach paired with difference-in-differences analysis find that an increase in Beijing’s public transport fare led to a short run increase in air pollution of approximately 16 percent. Fully understanding how public transport prices and in particular a price reduction via subsidized tickets impact air quality, however, is crucial, as price adjustments might offer an easy to implement measure for policymakers to reduce air pollution - especially in spatially constrained cities where extending existing networks or constructing new ones might not be an option.

Based on previous literature, we would expect a price reduction, as studied in our setting, to reduce air pollution. However, conclusive and causal evidence directly studying the impact of a public transport subsidy does not exist. To the best of our knowledge, our paper thus is the first to causally isolate the effect of an actual policy intervention in the form of a public transport subsidy on air pollution, thereby providing evidence on how a price reduction actually impacts air quality. Further, in contrast to previous research on the relation of public transport and air quality we provide evidence for a whole country, i.e. Germany, and not only selected cities.

Our research therefore contributes to fully understanding the effects of a price subsidy for public transport on air quality and thus is crucial for research and policy alike. In particular, our results may have important policy and health implications: they show that subsidizing public transportation might be a viable option to reduce air pollution particularly in cities, thereby contributing to the UN’s sustainability goal of creating more resilient, safer and healthier urban agglomerations. For instance, reductions in air

pollution have been shown to substantially reduce cardiovascular diagnoses (Margaryan, 2021) and improve infant health (Knittel et al., 2016).

In order to analyze whether a reduction in public transport prices ultimately reduces air pollution and to elicit causal effects of the subsidy’s introduction on air quality, the empirical strategy of the paper adopts a difference-in-differences approach. More precisely, the empirical setting compares changes in air quality between months May and June in previous, non-treatment years to changes in air quality for those two months in the treatment year 2022. We construct a state of the art air pollution index also used by the European Environmental Agency and show that the index decreases by about six to seven percent in response to the introduction of the ticket. Further, we document effect heterogeneity and show that the effect is largest in urban areas, during work days, in areas with high levels of public transport provision and stations measuring pollution directly stemming from traffic.

The remainder of the paper is structured as followed. Section 2 provides the relevant institutional background. Section 3 introduces the different data sources used for estimation and presents the estimation approach. Section 4 presents and discusses the results and Section 5 concludes.

2 Institutional Background

The 2021 general election in Germany resulted in a new coalition government of Social Democrats (SDP), the Greens and the Liberals (FDP). The creation of a sustainable mobility sector was one of the topics highlighted in the new government coalition agreement.³ Since 2022 and particularly the start of the war in Ukraine living cost and in particular energy prices increased drastically, which prompted the government to pass a set of relief measures aiming to mitigate rising costs of living and energy prices. The 9ET was part of a second set of such relief measures seeking to, amongst others, maintain affordable means of transportation. Additionally, in particularly the co-governing Green party frequently emphasized the ticket’s potential to reduce carbon emissions and provide a more sustainable alternative for the mobility sector, as stipulated by the coalition agreement (Spiegel Online, 2022).

On February 23rd, 2022 a first relief package (“Erstes Entlastungspaket”) consisting of several relief measures such as temporary tax cuts was decided upon by the ruling coalition parties. After the start of the war in Ukraine one day later and the consequent steep increase in gas and oil prices in May, 2022 a second relief package was passed in the German Bundestag. This second set of relief measures included a reduction of the energy tax on fuel in order to help people commuting by cars. Figure A.1 in the

³see Coalition Agreement 2021.

Appendix depicts the development of gasoline and diesel prices in 2022. The beginning of the war in Ukraine was followed by a steep increase of all types of fuel prices. After reaching a peak at the beginning of March, the price stabilized at moderately lower levels until June 1st. The energy tax implied a temporary drop in fuel prices. However, diesel regained pre-tax prices just after a few days. Overall, prices for all types of fuel remained at a relatively high level especially compared to the rest of the year. Crucially, in our identification strategy presented in the following section we can control for daily fuel prices to account for these patterns and the tax cut.

In order to additionally compensate users of public transportation, the relief package also included the 9-Euro-Ticket. For a total price of nine Euros a month, it allows its holders to use most types of public transportation like buses, subways, and regional trains all over Germany. The ticket was available from June 1st, 2022 until the end of August of 2022.⁴ One of the aims of subsidizing public transportation was to foster its utilization and thereby to speed up sustainable transportation. Just before June 1st, about seven million tickets had been sold.⁵ By the end of June approximately 21 million tickets had been sold.⁶ Factoring in the roughly 9 million regular subscribers to monthly or yearly tickets whose fare is automatically reduced to 9 Euros from June to August, more than thirty million 9ETs are in circulation.

3 Data and Empirical Approach

In order to analyse the 9-Euro-ticket's impact on air pollution, we collect pollution measurements for three key pollutants and data on covariates that have been shown to influence air pollution, such as weather conditions and holidays. Crucially, we also collect data on fuel prices allowing us to fully account for the tax cut in fuel prices that was simulatenously introduced with the 9ET (see above). The remainder of this section firstly presents our different data sources to then introduce our empirical approach.

3.1 Data

Air pollution data We have access to air pollution data for months May and July from 2018 to 2022. The data is provided as hourly measures by the Federal Environmental Agency (Umweltbundesamt, 2022).⁷ We observe whether a measuring station is located close to a street (traffic station) or in quieter more residential areas (background

⁴See <https://www.bundesfinanzministerium.de/...html> for more information on the relief packages.

⁵See <https://www.handelsblatt.com/politik/deutschland/sonderticket-es...html>

⁶See <https://www.sueddeutsche.de/wirtschaft/9-euro-ticket-stau-tomtom-1.5612144>

⁷All data can be requested by directly writing to the Federal Environmental Agency or by using their API: <https://www.umweltbundesamt.de/daten/luft/luftdaten/doc>.

station). While the former provides information on air quality in relation to traffic, the latter rather indicates the general quality of the air in an area.⁸ We make use of this differentiation in our estimations: in our main specification we exclusively focus on air pollution concentrations measured by traffic stations, in order to test whether there indeed is a reduction in car traffic due to the 9ET. In a heterogeneity check, we exclusively focus on background stations where we expect the potential effect of the ticket to be smaller.⁹ Further, the data includes information on whether the station lies in rural, suburban or urban areas.

In order to assess air quality we look at the pollutants nitrogen dioxide (NO₂), particulate matter with diameter of 10 micrometer and smaller (PM₁₀), and particulates smaller than 2.5 micrometers (PM_{2.5}), which we then use to construct a daily air quality index (AQI), commonly used by national and international authorities in order to assess pollution levels and provide information on potential health impacts at local levels.¹⁰ We use this air quality index as our key outcome variable. For the construction of the AQI, we follow the Common Air Quality Index by the European Union (Van den Elshout et al., 2014), which bases the index on the core pollutants NO₂, PM₁₀, and PM_{2.5} for traffic stations and additionally O₃ (ozone) for background stations. The index itself takes on values between 0 and 100, which is then further classified into four categories from very low pollution (index number 0-25) to high pollution (index numbers 75-100).¹¹

Fuel prices We also collect data on local fuel prices. Since 2013, fuel stations have been obliged to report each and every change of fuel prices (specifically for diesel and gasoline) in real time to the Market Transparency Office for fuels (“Markttransparenzstelle für Kraftstoffe”) run by the German Cartel Office.¹² We aggregate all fuel prices to district level by taking the daily mean of all stations within each administrative entity.¹³

⁸Stations measuring air quality close to industrial sites are excluded in our data set.

⁹In our data set, 411 ground-level stations measure the concentration of NO₂, 360 stations measure PM₁₀ and 273 PM_{2.5}. One of the reasons why there are fewer measuring stations for PM_{2.5} is that the coverage of this pollutant has only started relatively recently and the measuring net is still being extended.

¹⁰The website http://www.airqualitynow.eu/comparing_home.php e.g. provides air quality indices for various cities in Europe.

¹¹Basically, the highest hourly value within a day of any of the three pollutants at each measuring site determines the index value. In order to make values between the pollutants comparable over days, we normalize each pollution value to an index value. As suggested by table 4 in Van den Elshout et al. (2014), we for example get an index value of 25 in cases when NO₂ is 50, PM₁₀ is 25 or PM_{2.5} is 15. Also note that Van den Elshout et al. (2014) introduce a fifth category for values above 100 by capping the index at 100. The upper cap of 100 bears the additional advantage of the AQI to control for outliers.

¹²For more information see <https://www.bundeskartellamt.de/EN/Economicsectors/MineralOil/MTU-Fuels/...>

¹³Real time and historic price data is provided at the following website: <https://creativecommons.tankerkoenig.de/>.

Meteorology When analyzing air quality data, it is critical to control for current weather conditions. Wind and rain tend to improve air quality, since they clean the air e.g. from pollutants such as particulates. We use weather data aggregated to daily levels to control for mean temperature, mean wind speed and total precipitation levels. In order to do so, we acquired measurements from about 3.000 stations from the German Meteorological Service (DWD Climate Data Center (CDC), 2022). Since measurement stations are independently located from air quality measuring stations, we follow the approach by Auffhammer and Kellogg (2011) to match the nearest air quality to weather station.¹⁴ Through this method, we are able to match about 99 percent of pollution observations to the weather variables of interest.

Regional and further controls In parts of the analyses, we use district specific data.¹⁵ In particular, the German Federal Office for Statistics provided us with district level data of the total mileage of regional and local trains as well as buses per district-specific population. This information originally stems from enterprises that are the suppliers of public transport. We use this information in our heterogeneity analysis to check whether effects differ across districts with low and high levels of public transport.

Furthermore, we construct variables that indicate whether a day falls on a weekend, a public holiday or school holidays.¹⁶ In order to be able to differentiate between effects in urban areas including their commuting zones, we resort to OECD definitions of functional urban areas (FUAs).¹⁷ Those are constructed based on commuters' daily movements and normally include a core, which is the center to which people commute to and the surrounding commuting zone (Dijkstra et al., 2022). In Germany, there are 96 FUAs in total.

3.2 Empirical Approach

The paper employs a difference-in-differences (DiD) design using month June as the treatment group and May as the control group. For the pre-treatment period we focus

¹⁴The approach conducts the following steps: After calculating Vincenty distances, we identify the ten closest weather stations to each pollution station within a 75 kilometer distance and a maximum elevation difference of 200 meters. Then, the "primary station" is chosen as the closest meteorology station with more than 50 percent of non-missing observations and matched to the pollution data. Following, missing values are filled by regressing non-missing weather observations of primary stations on weather measurements of the nine other closest stations and using the predicted values from these regressions. Missing values still remain in the case that one of the nine stations had a missing observation. In this case the above step is repeated using the eight closest stations. The number of stations is then subsequently lowered. For a more thorough description see Auffhammer and Kellogg (2011).

¹⁵In total there are 400 district level regional units in Germany.

¹⁶Information about state-level holidays and vacations are retrieved from <http://www.feiertage-api.de/> and <https://ferien-api.de/> respectively.

¹⁷Shapefiles can be downloaded from <https://www.oecd.org/regional/regional-statistics/functional-urban-areas.htm>.

on pollution measurements from years 2018 and 2019. We explicitly exclude years 2020 and 2021, as due to changes of COVID 19 restrictions in May and June 2020 and 2021 respectively there might be confounding factors influencing air pollution outcomes in these years.¹⁸ Equation 1 describes the approach in more detail.

$$p_{symd} = \alpha_s + \gamma_y + \zeta_d + \beta_1 June_m + \beta_2 June_m \cdot \gamma_{2022} + X'_{kymd} \theta + \epsilon_{kymd} \quad (1)$$

p_{symd} is the logarithm of the air quality index measured at station s , in year y for month m , at day of the week d . We regress this outcome on station level fixed effects, α_s , controlling for all potential time invariant station-specific observables and unobservables such as the number of lanes the station is placed at or the distance to rail tracks. Further, we include yearly fixed effects, γ_y , to control for general differences across years. We also control for day of the week fixed effects, ζ_d . This allows us to only compare pollutant levels at the same day of the week with one another. This is necessary as there are pollution trends across days of the week and thus comparing pollutant levels on a Wednesday and a Friday might falsely pick up a difference in pollution between years that can simply be attributed to these trends.¹⁹ We then include a dummy variable $June_m$, which is equal to one if the month of the observation is June. Interacting the June indicator with an indicator variable for the year 2022, i.e. γ_{2022} , then gives the difference-in-differences estimate for coefficient β_2 . This setup allows us to test whether there indeed is a change in air quality between May and June in 2022, i.e. the year when the 9ET was introduced, that goes beyond the changes observed between these two months in previous years that were not subject to such a policy intervention. In addition, we control for a matrix of covariates, X' , including an indicator variable for weekends and holidays respectively as well as linear and squared daily weather conditions in the vicinity of each pollution station such as wind speed, precipitation and temperatures, as these have been shown to influence pollution levels. Further, we control for daily average fuel prices and interact the fuel prices with the year fixed effects in order to account for different effects across years. Controlling for fuel prices is crucial as at the same time as the 9ET a fuel tax cut was introduced (see Section 2). As detailed above, fuel prices fell in response to the tax cut, however, compared to the yearly trend only moderately (see Figure A.1). In the robustness checks of the paper we also present specifications excluding the first days in June and the last days in May to account for the temporary fall in gasoline prices and potential anticipation effects, which could entail that individuals drove less before June

¹⁸For example, in most federal states in-class teaching only restarted in late May/June in 2021 and mid and late May in 2020

¹⁹For example, on Fridays there may be a higher tendency to work from home.

in order to wait for a fall in gas and public transport prices. ϵ_{kymd} is the error term, which is clustered at the district level in our main specification.

The difference-in-differences approach presented above identifies the causal effect of the 9ET on air pollution if pollutant levels for a given day of the week in May and June 2022, in the absence of the introduction of the 9-Euro-Ticket, would have developed parallelly. We can check this assumption by carefully examining air pollution averages for both months before the ticket was introduced and after the ticket was introduced, as will be presented in the next section. In addition, together with our main results we also provide a placebo test where the reform date is shifted forward to 2019, thereby explicitly testing for common pre-trends using years 2018-2019.

4 Results

Descriptive Results We can check the identifying assumption by comparing pre-trends, i.e. air quality before 2022 for treatment (June) and control month (May). More precisely, we compare average values for a given day of the week in May and June before and after the introduction of the 9-Euro-ticket as we control for days of the week fixed effects in our main specification. Figure 1 shows the day of the week specific average for the logarithm of the air quality index for the pre-policy period, i.e. 2018-2019 (left), and the post policy period (right), i.e. the year 2022, respectively. The graph illustrates that when assessing pre-trends it is crucial to only compare pollutant levels at the same day of the week with one another, as there are clear general patterns in the average pollutant levels for a certain day of the week. For example, in general there appears to be a greater level of pollution in the middle of the week and lower levels over weekends.

Figure 1 supports our identification assumption: during the pre-treatment period, air quality index values for treatment and control months behaved relatively similarly and followed a parallel trajectory, throughout the week, albeit at slightly different levels. The corresponding average values for working days depicted in the textbox show that on average pollution on working days in June is 0.03 log points lower than in May. Looking at the post treatment period, i.e. the year 2022, we can see that average pollution for the control month May follows a similar weekly trajectory as in the pre-treatment period, albeit at an overall lower level. However, in contrast, average pollution falls substantially for the treatment month. In particular, during the week there appears to be a sharp decline in the log of the AQI in 2022, which suggests an improvement in air quality. This is further confirmed by comparing the average log values of the air quality index for working days, i.e. Monday to Friday, in May and June in the post-treatment period, as presented in the textbox: on average air pollution is 0.11 log points smaller in June than in May 2022 - a difference substantially larger than during the pre-treatment period.

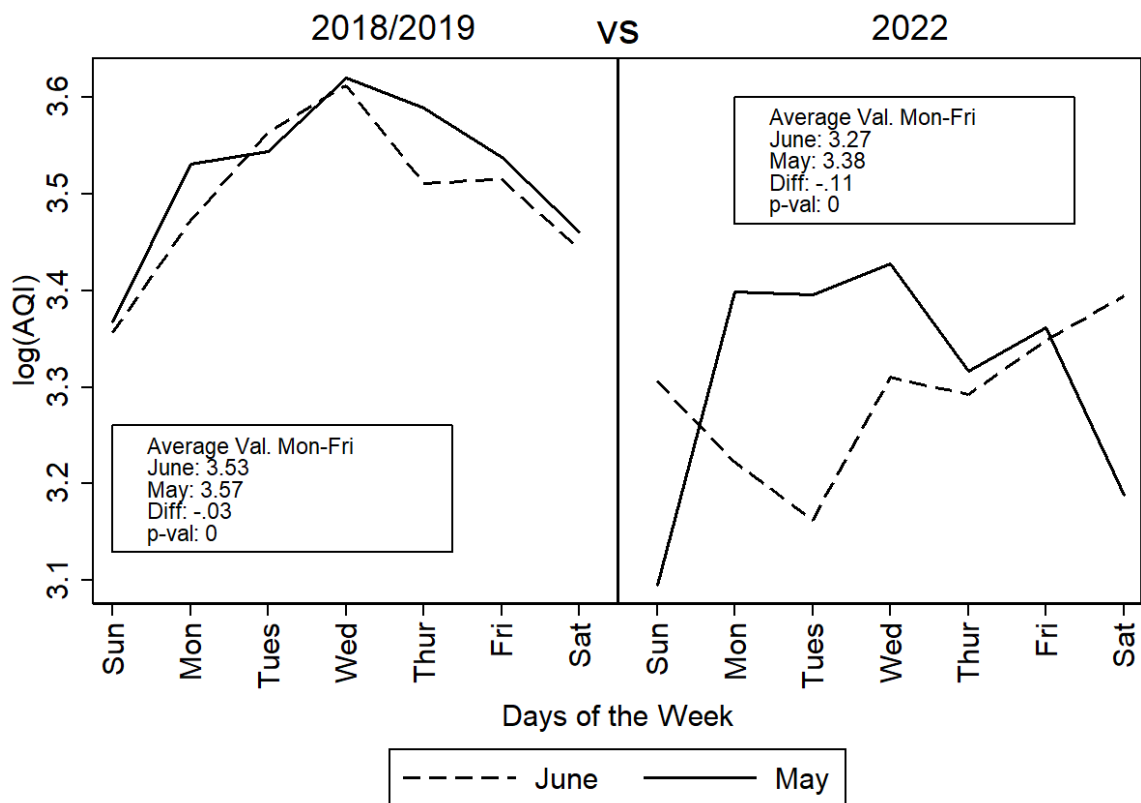


Figure 1: Day of the week averages for $\log(\text{AQI})$.

Note: Day of the week averages for $\log(\text{AQI})$ before and after the introduction of the 9-Euro-ticket for treatment (June) vs. control month (May). Average working day values and differences for May and June before and after the reform are displayed in the graph's textboxes. The p-values are derived from a two-sided t-test on the difference between both values. Corresponding values for weekends are 2018/19: June= 3.414, May= 3.402, Diff= 0.0124, p-value= 0.32; 2022: June= 3.349, May= 3.136, Diff= 0.214, p-value= 0.00.

Table 1: Main Results: log(AQI)

	(1)	(2)	(3)	(4)	(5)
Interaction	-0.0476* (0.0247)	-0.0473* (0.0248)	-0.0980*** (0.0237)	-0.0642*** (0.0236)	0.0154 (0.0144)
Covariates	No	No	No	Yes	Yes
Day of Week FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Station FE	No	No	Yes	Yes	Yes
Observed Years	18,19,22	18,19,22	18,19,22	18,19,22	18,19
Observations	24,268	24,268	24,268	24,103	16,068

Note: Source: own calculations. Standard errors in parentheses and clustered at district level, significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table displays regression results using the log of the air quality index as outcome variable. All specifications control for year specific fuel prices. Column (1) shows the results for a basic difference-in-differences approach. Columns (2)-(4) augment the estimation with additional fixed effects and covariates. Column (5) implements a placebo test where year 2019 is used as the new policy date.

In contrast, weekend average values in June in comparison to May visibly increase across pre- and post-treatment years. In 2018/19 average pollution on weekends was 0.012 log points smaller in June. However, average pollution on weekends in June 2022 was 0.21 log points higher than in May 2022. Anecdotal evidence suggests that due to lower public transport prices for regional trains there was a substantial influx in train travel over weekends (Zeit Online, 2022). In particular students and young people are said to have used trains increasingly for weekend trips and holidays, leading to newspaper articles about and TV coverage concerning crowded and delayed trains. This potentially had a deterring effect on travellers who might have switched to car use in order to avoid crowded trains, which could possibly explain the observed increase on weekends.

We then proceed by estimating our main specification and presenting our main results. Following the visual inspection of the graphs, we expect a negative effect of the 9ET on air pollution during weekdays and a positive effect during weekends. Further, we revisit our identification assumption by explicitly testing for common pre-trends conditional on covariates and fixed effects using a placebo framework solely focussing on the years 2018/19.

Main Results: Table 1 presents the results using log(AQI) as an outcome variable. In all specifications we control for daily fuel prices in order to account for the tax rebate in fuel prices introduced at the same time as the 9ET. Specification (1) shows the results for a basic difference-in-differences approach including a post treatment indicator for the year 2022, the monthly fixed effect for June and the interaction between both. We find

a negative point estimate for the interaction term suggesting that the average AQI fell by just under five percent. The estimated effect is significant at the ten percent level. Since an index value of 0 indicates the best possible air quality, the result suggests an overall average improvement in air quality. In specification (2) we additionally include year fixed effects and day of the week fixed effects. The point estimate remains similar in size and continues to be significant at the ten percent level. Finally, in specifications (3) and (4) we include station fixed effects and covariates, such as the weather conditions and variables controlling for public and school holidays. In specification (3) we find a relatively large and highly significant effect implying an approximate change of just under ten percent. In specification (4), when including the full range of covariates and fixed effects, the point estimate slightly decreases in absolute value to -0.0642 and remains highly significant at the one percent level. Thus our most restrictive specification, using the full set of covariates and fixed effects, points towards a fall in air pollution by more than six percent.

Lastly, in column (5) we repeat our preferred specification, i.e. the specification used in column (4), for the years 2018 and 2019 only. Crucially, we treat year 2019 as if the 9-Euro-Ticket was introduced in June 2019. This allows us to run a placebo test and explicitly test for the common pre-trend assumption. The point estimate is positive and insignificant, thereby supporting the notion that there is no systematic difference between treatment and control months across years previous to the actual introduction of the ticket.

All in all the results indicate a substantial fall in the air quality index of more than six percent. In order to relate the size of the effect to general trends in air quality, we can compare the air quality index in May/June 2018 and May/June 2019 with one another. We observe an overall yearly reduction of about ten percent in the index, when controlling for weather conditions and holidays. This is in line with a generally decreasing air pollution trend for Germany.²⁰ Our results thus suggest that the 9ET has the potential to accelerate this trend.

Mechanisms and Heterogeneous Results In a next step, we split our sample along several dimensions to analyze heterogeneous effects and potential mechanisms. Table 2 depicts the results. All specifications control for the full set of covariates and fixed effects. First, in columns (1)-(4) we split our sample into the core of a functional urban area (FUA), the total FUA and non-FUA (rural) areas.²¹ The effect is driven by a substantial reduction in pollution in core areas. One potential explanation is that most jobs are situated in core areas. If more individuals commute to these core areas by public

²⁰See e.g. EEA Air Pollution: Germany

²¹The total FUA includes the core as well as the commuting zone of a FUA.

transport there will be less traffic and congestion in these areas implying a fall in pollution concentration levels. Another possible explanation is that there is more supply of public transport in these areas, which would then allow for an easier switch to public means of transportation.

In order to generally assess the role of public transport supply, we split our sample into districts with a relatively high and low level of public transport infrastructure (see columns (5)-(6)). We can do so by using the aforementioned data on public transport kilometers per population for districts in Germany. More precisely, we split our sample into districts in the highest 25 percentiles of public transport kilometers per person and the lowest 75 percentiles. The results show that for both groups we find significant effects at the ten and five percent level respectively. As expected the effect size is more pronounced for the group with higher levels of public transportation.

Next, in columns (7)-(8) we confirm what the visual examination above indicated: the effect is driven exclusively by weekdays. For weekends we find a positive, albeit insignificant effect when including the full set of covariates and fixed effects.

Unfortunately, we do not have access to data on the mode of transportation and whether individuals switched in response to the introduction of the ticket. Therefore we do not see whether such a modal switch is the cause of the improvement in air quality. However, in our data we can differentiate between air quality measured by stations directly next to roads and background measurements in quieter areas. If there indeed is less traffic due to more individuals using public transport, the effect at stations directly exposed to traffic should be stronger. In our main specifications we have so far exclusively focused on traffic stations. In column (9) of Table 2 we repeat our estimation for background stations. Only using background stations we would expect a smaller or zero effect size, as these stations are not directly positioned next to streets. The results confirm this notion, as the point estimates now is positive, relatively small and insignificant.

Table 2: Heterogeneous Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Core FUA	Non Core	FUA	Non FUA	High PT	Low PT	Weekend	Weekday	Background St.
Interaction	-0.0863*** (0.0233)	0.0095 (0.0610)	-0.0708*** (0.0219)	0.0033 (0.0965)	-0.0791* (0.0403)	-0.0589** (0.0270)	0.0259 (0.0387)	-0.1020*** (0.0248)	0.0101 (0.0155)
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,700	4,403	21,814	2,289	6,051	18,052	6,840	17,263	46,914

Note: Source: own calculations. Standard errors in parentheses and clustered at district level, significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The table displays regression results using the log of the air quality index as outcome variable. Column (1) shows the results for stations from the core of functional urban areas, column(2) for stations positioned outside the core. Specification (3) just includes observations from functional urban areas and specification (4) from outside these areas. (5) solely uses measurements from stations in districts with a high level of public transport supply and (6) in districts with a low level. (7) and (8) split the sample into weekdays and weekends and (9) solely includes measurements from background stations. All specifications control for the full set of covariates and fixed effects.

Robustness In the Appendix we repeat our main estimation for different standard error clusters, i.e. at the station specific level and at the station-year level. Tables A.1 and A.2 show the results. Inference and statistical significance do not change across these different clusters.

Further, as detailed in Section 2, in addition to the 9ET, a tax cut on gasoline prices was implemented from June, 1st. The corresponding law, however, was already passed on May 19th, 2022. Car owners thus might have waited for June 1st in order to purchase new fuel and drive again. As a consequence pollution levels directly before June 1st might have been slightly dampened and heightened at the beginning of June, leading to a lower estimated decrease in pollutants after the introduction of the 9ET. In order to analyze these potential anticipation effects in the run up to June 1st, we repeat our main estimation for the log(AQI) in a leave-one-out exercise. Here we successively drop the first and last two days in May and June respectively. The results, presented in Table A.3 in the Appendix, indicate no substantial difference in the point estimates for the variable of interest, which remain very similar in size across specifications.

Lastly, we use each pollutant that contributes to the air quality index as a outcome variable separately, in order to check that it is not simply the construction method of the air pollution index that drives the results. Table A.4 in the Appendix shows the results for PM_{10} , $PM_{2.5}$ and NO_2 respectively. All point estimates are significant and negative supporting the results in the main specification using the air quality index as the key measure for air quality.

5 Conclusion

In this paper, we provide novel causal evidence on the effect of a large scale public transport subsidy on air pollution. The policy we study is unique in the sense that it reduced public transport fares for a whole country in some areas by as much as 90 percent. To the best of our knowledge, we are the first to causally study the effects of a public transport subsidy on air pollution, thereby expanding previous literature, which has so far predominantly focussed on price increases (Yang and Tang, 2018), calibrated quantitative models (Borck, 2019) or leveraged natural experiments such as unexpected public transit strikes (Bauernschuster et al., 2017) to study the general relationship between public transport and air pollution.

As our key finding, we show that pollution levels measured by a state of the art air pollution index fall in response to the policy intervention. In particular, the air pollution index decreases by approximately six to seven percent. Further, we document effect heterogeneity showing that the effects are largest during the week, i.e. when individuals commute to and from work. We also show that the effects are more pronounced in urban areas and regions with a well developed public transport network.

Our results are relevant for policymakers and researchers alike. First, our findings suggest that subsidizing public transportation can indeed incentivize a modal switch, which sparks a decrease in pollution levels and potentially other outcomes not studied in this paper such as carbon emissions. Further, the results echo findings of quantitative equilibrium models e.g. by Borck (2019), who also finds a decrease in pollution in response to lifting public transport fares all together. Our effect sizes lie in between the relatively small effect of public transport on air pollution documented in general equilibrium models by Borck (2019) and relatively large effects found in other papers studying price changes in public transport fares such as Yang and Tang (2018). The differences in effect sizes is plausible, as we estimate the short-term impact of the subsidy and can hence not account for long term equilibrium effects, which might work in offsetting directions.²² Further, we focus on pollution measurements across Germany, whereas other papers have singled out large urban agglomerations where a stronger relationship between public transport and air pollution seems plausible, and indeed is also shown in our heterogeneity analyses.

More generally, the documented effect might have important health implications. Margaryan (2021), for example, shows that a three percent decrease in particulates implies a fall of approximately two percent in the number of patients with cardiovascular diagnoses. Overall, the findings thus indicate that subsidizing public transport might be a viable option to reduce pollution in the short term and given results by Borck (2019) potentially also in the long term. Thereby, a policy intervention such as the 9-Euro-ticket

²²In particular, (Borck, 2019), in his model, emphasizes relocation mechanisms and an increase in housing consumption and residential emissions.

may indeed contribute to the UN's sustainability goal of creating more resilient, safer and healthier urban agglomerations.

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Appendix

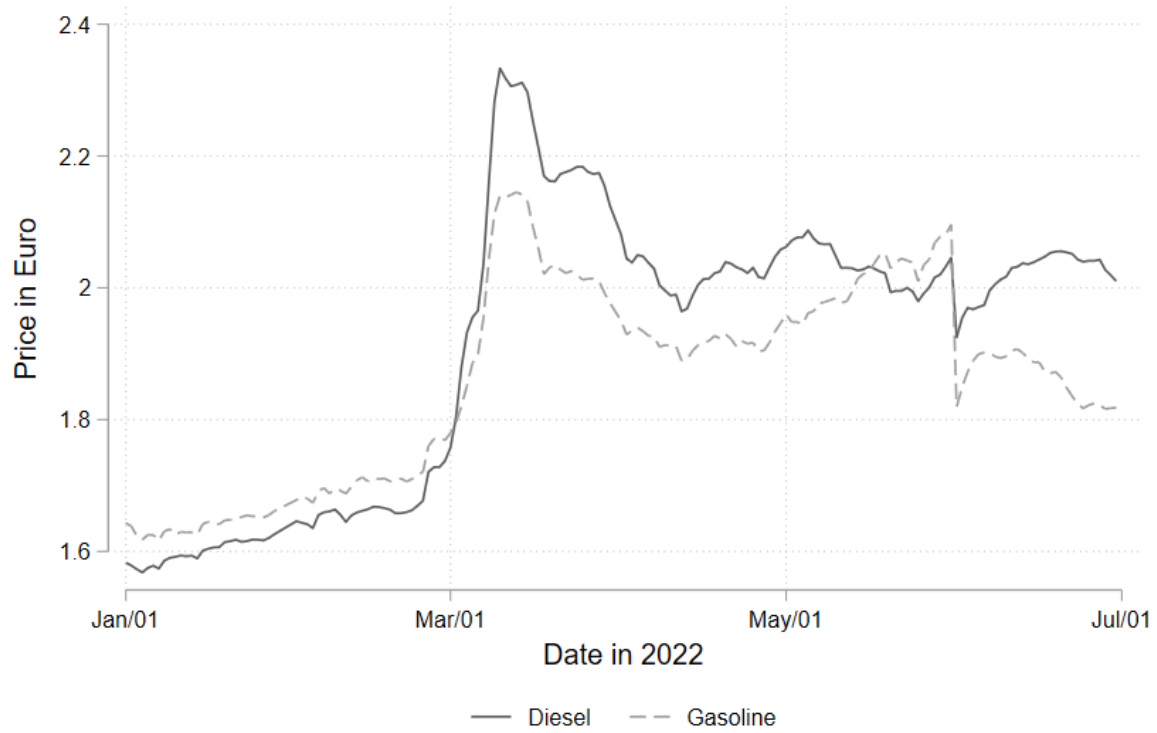


Figure A.1: Development of average gasoline and diesel prices in Germany, 2022

Table A.1: Results for SE Station Clusters

	(1)	(2)	(3)	(4)	(5)
Interaction	-0.0476* (0.0247)	-0.0473* (0.0248)	-0.0980*** (0.0237)	-0.0642*** (0.0236)	0.0154 (0.0144)
Covariates	No	No	No	Yes	Yes
Day of Week FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Station FE	No	No	Yes	Yes	Yes
Observed Years	18,19,22	18,19,22	18,19,22	18,19,22	18,19
Observations	24,268	24,268	24,268	24,103	16068

Note: Source: Own calculations. Standard errors in parantheses and clustered at district level, significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.. The table displays regression results using the log of the air quality index as outcome variable. All specifications control for year specific fuel prices. Column (1) shows the results for a basic difference-in-differences approach. Columns (2)-(4) augment the estimation with additional fixed effects and covariates. Column (5) implements a placebo test where year 2019 is used as the new policy date.

Table A.2: Results for SE Station-Year Clusters

	(1)	(2)	(3)	(4)	(5)
Interaction	-0.0476* (0.0247)	-0.0473* (0.0248)	-0.0980*** (0.0237)	-0.0642*** (0.0236)	0.0154 (0.0144)
Covariates	No	No	No	Yes	Yes
Day of Week FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Station FE	No	No	Yes	Yes	Yes
Observed Years	18,19,22	18,19,22	18,19,22	18,19,22	18,19
Observations	24,268	24,268	24,268	24,103	16068

Note: Own calculations. Standard errors in parantheses and clustered at district level, significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.. The table displays regression results using the log of the air quality index as outcome variable. All specifications control for year specific fuel prices. Column (1) shows the results for a basic difference-in-differences approach. Columns (2)-(4) augment the estimation with additional fixed effects and covariates. Column (5) implements a placebo test where year 2019 is used as the new policy date.

Table A.3: Leave-One-Out Results

	(1)	(2)	(3)
Interaction	-0.0642*** (0.0236)	-0.0645*** (0.0241)	-0.0630** (0.0242)
Covariates	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Station FE	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes
Observations	24,103	23,837	23,572

Note: Standard errors in parentheses and clustered at district level, significance levels * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.. Outcome variable is the log of the air quality index. (1) leaves out no observations before and after the introduction, (2) the first day on each side and (3) the first two days on each side. All specifications control for the full set of covariates and fixed effects.

Table A.4: Results for Different Air Pollutants

	(1) log(PM ₁₀)	(2) log(PM _{2.5})	(3) log(NO ₂)
Interaction	-0.0511** (0.0231)	-0.1057*** (0.0320)	-0.0380* (0.0227)
Covariates	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Station FE	Yes	Yes	Yes
Day of Week FE	Yes	Yes	Yes
Observations	19,925	12,179	23,142

Note: Own calculations. Standard errors in parantheses and clustered at district level, significance levels* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.. All specifications control for year specific fuel prices.