Empirical Essays on Spatial Heterogeneities and Impact Evaluations

Von der Mercator School of Management, Fakultät für Betriebswirtschaftslehre, der

Universität Duisburg-Essen

zur Erlangung des akademischen Grades

eines Doktors der Wirtschaftswissenschaft (Dr. rer. oec.)

genehmigte Dissertation

von

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aus

Müllheim

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Tag der mündlichen Prüfung: 12. April 2024

Cumulative Dissertation - Current Status of Each Chapter

Chapter 1: Evaluation of Railroad Noise: The Proximity to Railroads and Its Effect on House Prices

A similar version of this chapter has been published as Thiel, P. (2022). Evaluation of Railroad Noise: The Proximity to Railroads and Its Effects on House Prices. *Ruhr Economic Papers No. 981*. https://doi.org/10.4419/96973-146.

Chapter 2: Housing Prices, Airport Noise and an Unforeseeable Event of Silence *(joint work with Philipp Breidenbach)*

A similar version of this chapter has been published as Breidenbach, P. and Thiel, P. (2023). Housing Prices, Airport Noise and an Unforeseeable Event of Silence. *Ruhr Economic Papers No. 1020*. https://doi.org/10.4419/96-973186. The chapter has also been invited for resubmission to the *Journal of Housing Economics*.

Chapter 3: Heterogeneous Pass-Through Over Time and Space: The Case of Germany's Fuel Tax Discount *(joint work with Manuel Frondel and Colin Vance)*

Acknowledgment

This thesis would not have been possible without the comments, suggestions, and support of my supervisors, colleagues, friends, and family.

First of all, I would like to thank my supervisors, Tobias Seidel and Thomas K. Bauer, for their academic guidance throughout my Ph.D. journey. Their comments, suggestions, and ideas have dramatically improved this work.

I would also like to thank the RWI and the Ruhr Graduate School for providing me with the academic, technical, and financial resources that made this Ph.D. possible in the first place. I benefited from the excellent courses offered, the frequent seminars, and the opportunity to attend several international conferences and workshops. Furthermore, I appreciate the support of the entire team of the Research Data Center FDZ Ruhr. Special thanks go to Sandra Schaffner, Philipp Breidenbach, Fabian Dehos, Matthias Kaeding, Lukas Hörnig, and Yvonne Meyer, who were always open for discussions, gave tips, and helped with administrative issues. I would also like to thank Thorben Wiebe for excellent research assistance and endless coding discussions.

I also benefited from extensive discussions with my co-authors, Philipp Breidenbach, Manuel Frondel, and Colin Vance, who were never reluctant to chat, exchange ideas, and work out strategies for moving forward.

Above all, I would like to thank my family for their unconditional support in getting me through this Ph.D. program. I am especially grateful to my wife Anne, my mom, my sister Nadja, and my brother Thomas. Without you, this would not have been possible.

Essen, January 2024

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Introduction

Establishing causal inferences in contemporary urban economic analysis, particularly with regard to the dispersion of local preferences and their heterogeneity, requires extensive data sets with precise spatial and temporal information. This assessment must be conducted systematically, regardless of the lens through which it is undertaken, be it political or scientific. It is important to acknowledge that no spatial unit operates in isolation, underscoring the possibility that neighboring units may exhibit significant adaptation and similarity yet also manifest differences. This holds particularly true for Germany, a country with a high population density on the one hand but also sparsely populated areas on the other hand, leading to patterns of both regional similarity and dissimilarity. The presence of spatial diversity poses two challenges when working in spatial settings. Firstly, proximity results in local and regional spillover effects that create clusters of estimated effects. These spillovers dilute the true treatment effects such that precise information is required to identify the impact of the setting at hand. Secondly, spatial heterogeneities arising from regional idiosyncrasies lead to varying effects.

Notably, not all urban variables can be measured directly and may only be approximated, further complicating these considerations. For example, access to amenities such as green areas or the impact of environmental noise, a disamenity, are often present in regional settings but cannot be measured directly, an issue discussed in Chapters 1 and 2. To capture the impact of neighborhood amenities and disamenities, economists use strategies such as the hedonic price framework, which assumes that housing market prices incorporate local variables.

Policymakers must also address these challenges. Although national strategies are implemented throughout the entire country, their uniform implementation does not necessarily result in equal effects across different regions - a theme encountered multiple times in the subsequent chapters.

In Chapter 1, I examine railroad noise, a frequently encountered disamenity, and its relationship to property values. The Railroad Noise Protection Act (RNPA), a recent legislation enacted by the German government, intends to mitigate the impacts of railroad noise by banning noisy freight trains from using the German rail network by 2020. I use this situation and the spatial and temporal variation it produces to assess the value of noise reductions for residents near the railway tracks. I analyze high-resolution data on house prices and detailed neighborhood variables and employ high-resolution geographical information on major freight train routes in Germany. To identify the impact of noise reduction, I utilize a difference-in-differences approach with a hedonic price function. Considering the RNPA's gradual implementation, it is evident that its mere declaration and the gradual process of removing loud freight trains increased house prices in (formerly) affected areas by 0.5% ($\approx$ 2,042 Euro), while the full prohibition in 2020 resulted in an additional 2.5% ($\approx$ 12,443 Euro) increase. This price surge underscores the significant impact of the RNPA on the real estate market and the value of noise reductions in general. The heterogeneity analysis indicates that positive effects decrease with the distance from railroad tracks, and there is no measurable effect beyond 1km. However, the study also demonstrates that locations that are generally exposed to high levels of noise, not only from railways but also from airports, industrial plants, and streets, benefit the most from the RNPA policy. Banning loud freight trains results in price increases of up to 6.9%, significantly surpassing the baseline impact. Even though the RNPA only addresses one major noise source, the large magnitude of effect in areas affected by multiple noise sources underscores the importance and effectiveness of targeted policies.

Chapter 2 (co-authored with Philipp Breidenbach) expands on the topic of noise pollution, building on the understanding gained in Chapter 1. Rather than concentrating solely on railroad noise, this chapter examines the impact of aircraft noise. While Chapter 1 analyzes the effect of proximity to railroad tracks and the impact of the RNPA, we utilize strategic noise maps to differentiate between those impacted and those unaffected by air-traffic noise. To establish a quasi-experimental design, we leverage the Covid-19 pandemic as an exogenous event. The pandemic's impact on the airline industry was unprecedented and severe, causing a significant paralysis of the flight business. Even after the most critical situation had passed, the aviation industry remained troubled - as evidenced by an auxiliary analysis of stock market values. By utilizing a difference-in-difference framework and an event-study analysis, along with comprehensive data on housing values, our findings demonstrate a 2.3% rise in prices for (formerly) noise-treated apartments during the quieter times. Examining the temporal pattern more closely, the effect accelerates over time, only to dissipate at the end of our observation period. In the summer of 2020, the positive impact is roughly 4%, which reaches its peak at 6% in 2021. The detectable effect only decays in 2022. The almost immediate responses found weaken the general story of sticky housing markets. Furthermore, the particularly strong effects observed in 2021 may not be solely attributed to the mere reduction of noise. Another possible explanation is information asymmetries, in which out-of-town buyers pay a price premium for quietness without knowing the past and potential future noise levels. Additionally, the significant impact in 2021 can also be linked to the aviation industry's future developments and the altered perception towards it.

Chapter 3 (co-authored with Manuel Frondel and Colin Vance) moves away from the (dis-) amenity focus but stays within the realm of policy evaluations. In the spring of 2022, fuel prices surged in many regions of Germany, exceeding 2 Euros per liter. The German government responded to the burden of the increasing energy prices by introducing the Fuel Tax Discount (FTD), which temporarily reduces energy taxes by 35.16 cents per liter for petrol and 16.71 cents for diesel. This chapter aims to address two key questions: whether the tax reductions have been passed on to all consumers and whether any variations exist over time and space. We analyze the general pass-through rates of tax reductions and compare them with different settings in terms of supplier competition, variations in demand elasticity, and public awareness on the consumer side. Based on high-frequency data for Germany and France, we discover pass-through rates of 96% for diesel and 86% for petrol, suggesting a high efficacy of the policy intervention. However, dissecting the effects further reveals that the pass-through decreases over time, resulting in only small fractions being transmitted at the end of the FTD period. Our study demonstrates that the initial high compliance may be attributed to the high public attention indirectly influencing gas stations to transmit the FTD. However, once the attention wanes, the pass-through also diminishes. Furthermore, we find that not all regions can benefit from the same reduction in fuel prices, as there is great heterogeneity across different locations. We demonstrate that low-income regions receive greater benefits from FTD compared to high-income regions, reflecting the distributional impact of FTD. Nevertheless, the diminishing effects over time persist in this context.

All three chapters demonstrate the potential for large-scale (political and non-political) interventions to be effective. However, the extent of their effectiveness is contingent on regional and temporal factors, resulting in variations in policy implementation and outcomes at the local level.

CHAPTER 1

Evaluation of Railroad Noise: The Proximity to Railroads and Its Effect on House Prices

Chapter Abstract

In 2017, the German federal government enacted the Railroad Noise Protection Act to diminish noise from freight trains. This study assesses the legislature's impact on residential property values through regional analysis of affected properties proximate to railway tracks and residences at a greater distance before and following the enactment of the national policy. The difference-in-difference analysis indicates that homes located near the tracks experience an increase in house prices ranging from 0.5% to 2.5%, depending on the time periods considered for the passing and implementation of the act. An assessment of heterogeneity demonstrates that the favorable impact of the Railroad Noise Protection Act intensifies as the distance to the tracks shortens. Moreover, individuals with the highest noise exposure, not just from railroads, benefit the most from the policy.

JEL codes: O18, Q53
Keywords: House prices, Hedonic price function, Railroad noise, Railroad Noise Protection Act.

A similar version of this chapter has been published as Thiel, P. (2022). Evaluation of Railroad Noise: The Proximity to Railroads and Its Effects on House Prices. *Ruhr Economic Papers No. 981*. https://doi.org/10.4419/96973146.

1.1 Introduction

Noise pollution is a major concern for many individuals, and the transportation sector is one of the primary contributors. Despite the convenience of being in proximity to transportation infrastructure, living nearby often prompts complaints about excessive noise and air pollution. High levels of environmental noise not only cause disturbance but also pose health risks (see, e.g., Münzel et al., 2014; Babisch et al., 2005; Vienneau et al., 2015). Prolonged exposure to high levels of noise has been linked to the development of cardiovascular diseases such as high blood pressure and increased heart rates. At the same time, it has a detrimental effect on sleep quality, which ultimately affects cognitive performance. In addition to these consequences on health and mental well-being, noise also contributes to discomfort affecting the overall quality of residential environments.

Assessing the impact of noise, which is considered a non-market good, is complicated by the limited availability of comprehensive data on the health and general satisfaction of people living near railroad tracks. The inclusion of a subjective element in direct measurement methods increases these difficulties. In addition, existing data are often not disaggregated to the fine-scale level necessary for a thorough evaluation of impacts. In response to these challenges, economists often use hedonic estimates derived from housing prices as methodological tool for assessing the value of non-market goods.

The study assesses railroad noise as a primary noise source and explores the connection between proximity to railroad tracks and house prices, utilizing the noise reduction gained from the Railroad Noise Protection Act (RNPA). The law was enacted by the German Federal Government in 2017 due to the harmful effects of high train noise levels. By 2020, freight trains with outdated brake systems are banned from German railroads in order to address the noise burden in close proximity to tracks. The switch from cast-iron brakes to composite brakes, also referred to as whisper brakes, has the potential to reduce noise levels by up to 10 decibels (dB) (Deutsche Bahn AG, 2021). This reduction translates to a significant improvement in terms of noise pollution and treatment intensity, making whisper brakes a valuable consideration for this study. The study seeks to understand preferences for specific residential locations under changing environmental noise levels, thus allowing for an assessment of the impact of rail noise on housing prices and the effectiveness of the RNPA.

The RNPA provides a distinct advantage as it applies to all areas of Germany affected by noise from freight trains. In contrast, alternative noise reduction measures, such as subsidizing building modernization or installing noise barriers, are more localized and selective. Access to funding for these countermeasures is dependent on the building's condition and not automatically available to all. In addition, the process of applying for funding is bureaucratic and requires justification for its necessity. The RNPA shifts responsibility to the noise producer and proposes a novel framework for promoting noise reduction aimed at all nearby residents, regardless of their geographic or social background.

Research examining the impact of noise pollution caused by rail transportation on real estate prices has consistently revealed negative effects. For instance, Theebe (2004) conducted a study on traffic noise in the Western Netherlands and found a negative correlation between noise pollution and house prices. Similarly, Andersson et al. (2010) investigated the impact of road and railroad noise in Sweden and detected a negative influence on housing prices, with a 0.4% decrease per decibel increase in railroad-related noise. Studies conducted in other regions, such as Norway (Strand and Vågnes, 2001) and South Korea (Chang and Kim, 2013), have found that greater distances from railroad tracks are associated with higher house prices, while increases in noise decrease home values. Ahlfeldt et al. (2019) focus on the capitalization effects of land prices by examining the access to and the noise generated by Berlin's urban railroad system. They also investigate the changes in these effects over the 20^{th} century. As individuals become wealthier, their appreciation for access to railroads and silence increases.

Certainly, railroads are not the only source of noise studied. Airports are also a significant topic in this field of research. According to a meta-analysis by Nelson (2004), air traffic noise is negatively associated with property prices. The findings of Jud and Winkler (2006); Cohen and Coughlin (2008, 2009), and Boes and Nüesch (2011) coincide with this negative relationship. Ahlfeldt and Maennig (2015) address differences in preferences regarding this inconvenience.

Another strand of literature examines the impact of proximity to noise sources on accessibility. Although living near railroad tracks exposes residents to noise, it also grants them immediate access to railroad-related services. The literature demonstrates that this accessibility premium positively affects housing prices. Examples include the analysis conducted by Brandt and Maennig (2012) on railway access in Hamburg, Germany; the research of Dubé et al. (2013) on the opening of commuter rail stations in Canada; the study of Bowes and Ihlanfeldt (2001) aiming to disentangle various channels related to accessibility; the meta-analysis by Debrezion et al. (2007); and the investigation by Debrezion et al. (2011) on the quality of railroad services at stations in the Netherlands. Considering the significance of access, including it in the analysis is crucial.

This study contributes to the existing literature in the following ways. First, many studies focus on a limited regional area (e.g., a specific city). This is often due to a lack of data. Typically, geographically referenced rail lines are not available, or the corresponding housing data are missing. This study uses the geographic locations of all six major freight rail corridors in Germany and links them to precisely geographically referenced housing units. The national coverage allows for general insights into noise mitigation assessments. Other settings, which are limited to certain areas, allow conclusions to be drawn only for these specific regions.

Second, this chapter provides insights into the effectiveness of a concrete noise policy intervention. While other measures, such as noise barriers, only aim to alleviate the outcomes of prolonged noise exposure, they do not address the root cause of noise production. Therefore, they only offer relief to a restricted population. This study contributes to the noise literature by demonstrating that a national strategy to counter high noise levels can positively impact affected residents. The introduction of the RNPA leads to a positive effect on house prices. Furthermore, the study highlights a symmetry of effects with respect to the noise literature, which often finds a negative correlation between noise and home prices. Ultimately, utilizing the RNPA offers the advantage of simultaneous treatment. There is no endogeneity in the assignment process since all residents in the treatment group (i.e., those living near the tracks), regardless of their social background and location, experience simultaneous benefits from the RNPA implementation.

Finally, railroad noise has received less attention than other sources, such as road noise. This is particularly true in Germany, where the relationship between railroad noise and property values is understudied. As far as I know, this research is the first to investigate the impact of railroad noise on property values on a large scale in Germany, whereas previous studies only investigated smaller areas, such as specific cities. Therefore, this study demonstrates that noise mitigation measures are not only necessary in urban settings but also provide relief in less densely populated regions.

I combine the geographic locations of homes with freight train corridor information to estimate a hedonic price function. I use regional variation to compare homes exposed to noise pollution (treatment group) to those that are not affected by freight train noise (control group) before and after the implementation of the RNPA. The baseline results indicate that house prices near railroad tracks have increased compared to those further away after the enactment of the RNPA. There was a 0.5% rise observable during the adoption period from July 2017 to November 2020, while after the full enactment of the RNPA in December 2020, there was a gain of 2.5%. The heterogeneity analysis suggests that noise-treated houses benefit the most from the RNPA, the closer they are to the tracks, i.e., the higher the noise levels. Further, the RNPA brings most relief to those with the highest total noise levels, not just from railroads. These findings are robust to several robustness checks, for instance, by restricting the setting to urban areas or specifying different functional forms.

The chapter is structured as follows: The background of the RNPA and its significance as a countermeasure for noise from freight trains are presented in Section 1.2. Section 1.3 outlines the empirical approach used to estimate the impact of the RNPA, the data sources employed, and it also offers descriptive statistics. Section 1.4 presents the outcomes of the baseline regression, outlines various robustness tests applied to validate these findings, and examines the impact under diverse settings. Section 1.5 provides a summary.

1.2 Background

Railroads are vital for transporting goods in Germany, with approximately 18% of goods being transported by train in 2020 (Federal Office of Statistics, 2021a). This places railroads as the second most crucial mode of transportation for goods, following transportation by truck. In line with German policymakers' drive towards a more environmentally friendly transportation sector, the importance of railroad transportation is anticipated to grow to 25% by 2030 (Federal Ministry of Transport and Digital Infrastructure, 2020). The rise in freight traffic on railroads as a substitute for truck transportation has a negative impact on residents living near these tracks. According to noise statistics from the Federal Railway Authority (FRA), 6.7% of the German population experiences some level of railway noise during daytime hours. This number increases to 11.9% at night (FRA, 2020).[1]

The FRA has installed measuring stations in close proximity to tracks, allowing for the monitoring of passing trains and the interpretation of train characteristics (FRA, 2022).[2] Freight trains exhibit an average transit exposure level of 84 dB and an average maximum noise level of 90 dB.[3] Compared to a typical conversation that measures 60 dB (Center for Disease Control and Prevention, 2019), a freight train tends to be louder by approximately 24 dB (or up to 30 dB for its maximum noise level). When analyzing noise differences, it is important to acknowledge that they are measured on a logarithmic scale, resulting in a disparity between the measured sound level and the perceived loudness. To facilitate the comprehension of sound level discrepancies, a general guideline is that a 10 dB increase corresponds to a doubling of the noise source's perceived loudness (Murphy and King, 2014). For the example of freight trains, a difference of 20 decibels to 30 decibels compared to a normal conversation indicates that the train is perceived as

[1]The noise annoyance threshold is set at 55 dB for daytime and 45 dB for nighttime. Thus, the increased percentage of individuals impacted at night can be attributed, in part, to the reduced detection threshold. Given that the sound level during the nighttime is generally lower, it is understandable that more individuals are impacted since this is a particularly sensitive period.

[2]The FRA presently supervises 19 stations, which cover approximately two-thirds of all freight train transport activity (FRA, 2022).

[3]The transit exposure level refers to the average sound pressure level (in decibels) produced by a train as it passes a certain location (Isert and Lutzenberger, 2020).

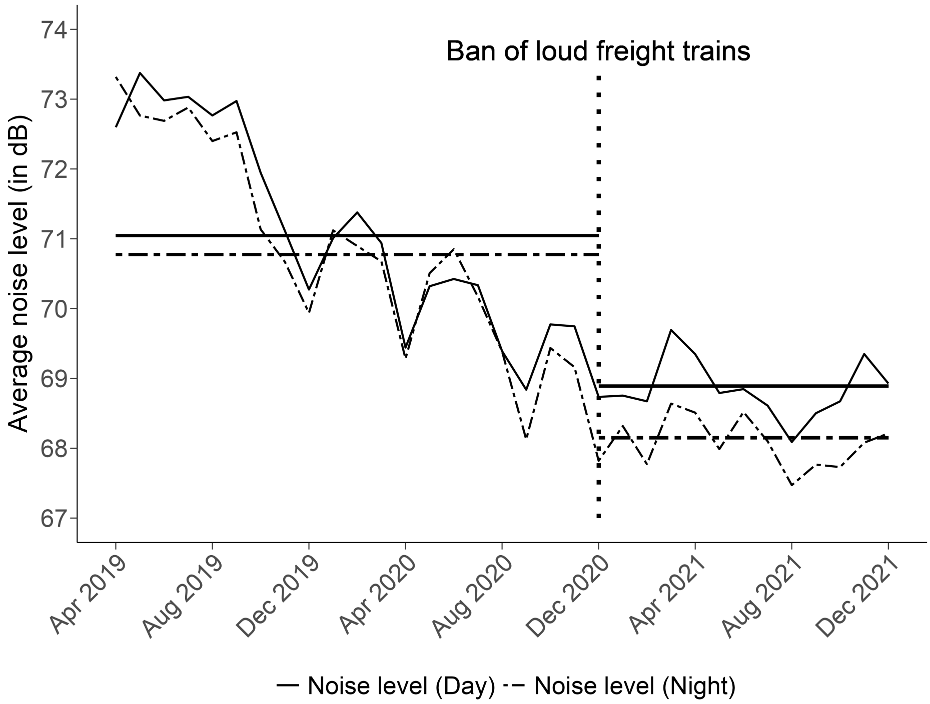
being four to eight times louder.

To alleviate the detrimental impact of excessive noise pollution for individuals residing near railway tracks, the federal government enacted the Railroad Noise Protection Act (RNPA) in July of 2017. Primarily, the legislation endeavors to prohibit the operation of noisy freight trains, effective December 2020 (Federal Ministry of Justice, 2017). However, during the interceding period between the bill's passage (July 2017) and enforcement (December 2020), train operators were obligated to modernize their vehicles by substituting cast-iron brakes with a newer composite alternative referred to as whisper brakes. The downside of using cast-iron brakes is that they tend to roughen the surface of the wheels, leading to increased friction between the wheels and the tracks over time. This results in a louder sound both during acceleration and braking. In contrast, composite brakes, which are made by blending materials such as rubber, metal, and resin (Allianz pro Schiene, 2022), help maintain a smoother surface that protects the wheels from damage, leading to quieter train rides. The use of whisper brakes can lead to a corresponding reduction in noise levels by up to 10 dB, resulting in a perceived loudness decrease by half (Deutsche Bahn AG, 2019). Therefore, this law is a significant strategy for reducing noise levels and creating a suitable setting for detecting causal effects in this study. Subsequent to December 2020, noncompliance with RNPA regulations can lead to fines of up to 50,000 Euros. Therefore, operators had strong incentives to modernize their fleet before the end of 2020. This paper refers to the period between July 2017 and November 2020 as the adoption phase and the period after December 2020 as the actual treatment phase.

Figure 1.1 offers descriptive evidence of the noise levels emitted by trains over time and for day and night periods using data from measuring stations of the FRA. The graph indicates a reduction in noise levels during the day and at night. Comparing the average levels before and after the RNPA's final implementation (December 2020), the results indicate a 2.2 dB and 2.6 dB reduction in daytime and nighttime noise levels, respectively (compare horizontal lines). Additionally, after December 2020, the night level is clearly below the day level. Previously, both levels were of similar magnitude.

The observation period for these noise measurements in Figure 1.1 starts in April 2019. The period covered in the analysis (June 2013 to June 2021) is not fully included since the measuring station network was only implemented in 2019. Therefore, I assume that noise levels prior to April 2019 were at least at the same level as those in the remainder of 2019. This appears reasonable since Deutsche Bahn, the largest railway services provider in Germany, intensified its efforts to convert to whisper brakes following the introduction of the RNPA. The Deutsche Bahn completed the modernization in 2020 (Deutsche Bahn AG, 2021).

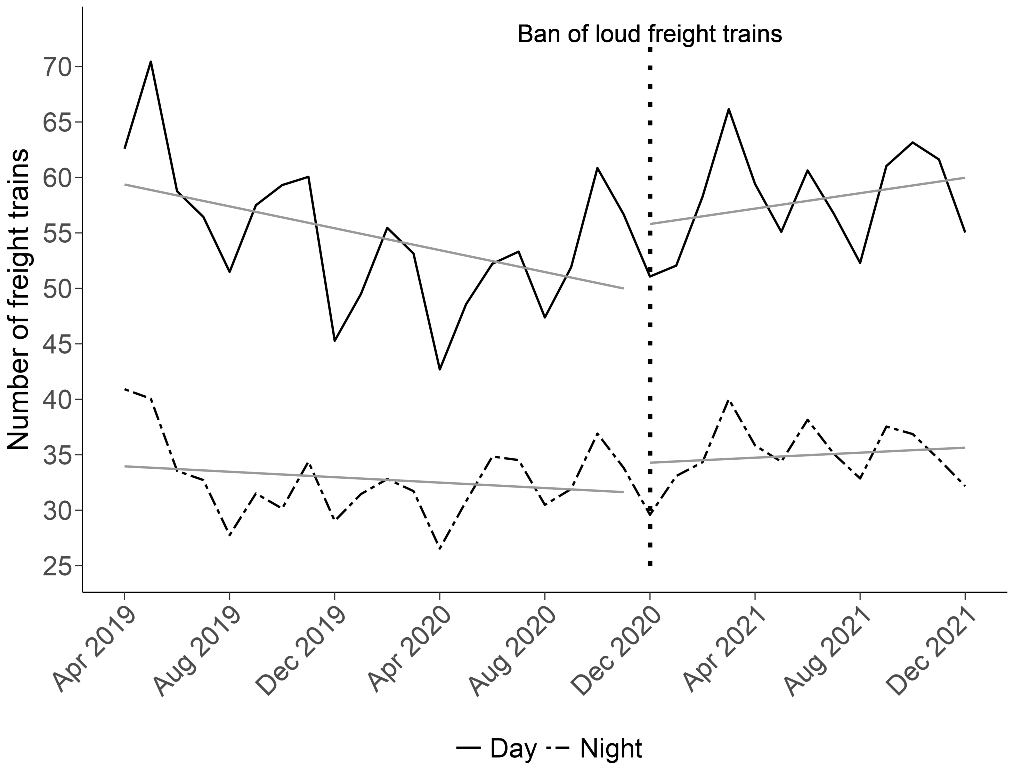
Figure 1.1: Development of Railroad Noise Levels over Time



Notes: The figure shows the average noise levels for the day (6 am to 10 pm) [solid lines] and night periods (10 pm to 6 am) [dashed lines] measured in dB based on the Day-Evening-Night index. The vertical dotted line indicates the full implementation of the RNPA in December 2020, resulting in a ban on noisy freight trains and the possibility of fines for non-compliance (Federal Ministry of Justice, 2017). The horizontal lines depict the average noise levels during the day and night, both before and after the complete implementation of the RNPA.
Source: Author's graph. The data is provided by the FRA (2022) and is based on measuring stations positioned near the railroad system.

The development of noise levels might also be partially attributable to the COVID-19 pandemic, which overlaps with the observation period. It is possible that the decrease in noise levels was due to restrictions on national and international trade, as well as limitations on travel and business activities caused by the pandemic. One could argue that the decrease in average noise levels is due to a reduction in the number of trains, potentially stemming from operators' reluctance to modernize their fleet. Figure 1.2 refutes both arguments by plotting the monthly average number of freight trains in Germany. The information is based on the same data set as the noise levels (FRA, 2022). It shows an increase in the number of freight trains, on average, after the RNPA has been fully adopted compared to previous periods.[4] Hence, the drop in noise levels cannot be related to a reduction in train activity.

Figure 1.2: Average Number of Freight Trains



Notes: The figure shows the average number of freight trains by month for day (6 am to 10 pm) [solid lines] and night periods (10 pm to 6 am) [dashed lines]. The horizontal lines in grey show the trend for the respective noise level and period. The vertical dotted line marks the complete adoption of the RNPA in December 2020. The chart corresponds directly to Figure 1.1.
Source: Author's graph. The data is given by the FRA (2022).

[4] The average monthly number of freight trains is 54.7 trains during the daytime and 32.8 trains during the nighttime before December 2020. Afterward, the number increased to 57.9 trains during the day and 35.1 trains at night.

1.3 Empirical Strategy and Data

1.3.1 Empirical Strategy

To assess the impact of implementing the RNPA on house prices by reducing noise, I employ a hedonic price function as per tradition (Rosen, 1974). Adhering to the notion that a house's price encompasses its features and surroundings, an implicit price is determined. The methodology allows for the measurement of the RNPA's efficacy and the resulting reduction in noise based on revealed preferences. This is due to the fact that (dis-)amenities, such as noise levels, are expected to be reflected in the housing prices.

The baseline setting applies the following equation:

$$\begin{aligned} ln(y_{ijt}) = X_{ij}\beta + \gamma Buffer500_i + \delta(LawPassed_t \text{ x } Buffer500_i) + \\ \theta(LawInForce_t \text{ x } Buffer500_i) + Month_t + Grid_j + \epsilon_{ijt}, \end{aligned} \quad (1.1)$$

where $ln(y_{ijt})$ is the logarithm of the listing price for house i in grid j and month t. X_{ij} is a vector of controls for each house, including the unit's characteristics[5], regional factors, distances to other noise sources, and accessibility variables (see Table 1.1 for an overview of the variables used and Table 1.2 for summary statistics). The variable $Buffer500_i$ indicates whether the house lies within 500 meters (m) from the tracks, capturing the treatment group.[6] The control group includes all observations above the 500 m threshold but still within the municipality crossed by the considered freight train corridors. Therefore, I exclude observations that are distant and potentially highly different from the treated housing units. I test the stability of this setup in the robustness checks. The $LawPassed_t$ variable is an indicator equal to one for the months spanning from July 2017 to November

[5]I include the following characteristics: Number of rooms, age of the building, number of floors, endowment, number of bathrooms, plot area, heating type, a dummy whether the building is still under construction, living space, and the building's condition. The characteristics age, living space, and plot area are also included as squared terms to account for the fact that the house prices most likely do not react linearly to changes in these variables. For an overview of all variables, see Table 1.1.

[6]The distance threshold of 500 m corresponds to around the 20^{th} percentile (approximately 496 m) when computing the proximity of each residence to the nearest railroad track. Alternative distance thresholds are also employed in the analysis of heterogeneity.

2020, corresponding to the RNPA's adoption period. Similarly, $LawInForce_t$ denotes the months between December 2020 and June 2021, representing the treatment period when the RNPA was fully implemented. Therefore, the coefficients of interest, represented by δ and θ, indicate the additional impact on housing prices for residing within a 500 m vicinity from the tracks in relation to residences located further away subsequent to the passing of RNPA (LawPassed$_t$ x Buffer500$_i$), and following the complete enforcement of the law (LawInForce$_t$ x Buffer500$_i$).

Splitting the treatment period into two time slots follows the intention to capture different treatment intensities. The RNPA implementation was carried out in two phases, beginning in July 2017 with train operators being given time until November 2020 to update their fleets. The modernization period is expected to result in a gradual decrease in noise levels. The law was enforced after December 2020, and non-compliance could result in sanctions. The noise levels should decrease compared to the previous period, as demonstrated by Figure 1.1. The first period can be interpreted as the adoption period, with δ capturing the adoption effect of the RNPA. In contrast, the second period represents the actual treatment period with the RNPA fully enrolled. One expects the effect of the interaction with $LawPassed_t$ to be smaller than for the period when the modernization has been completed ($LawInForce_t$) as the treatment intensity resulting from the RNPA is larger, and the noise levels are lower then.

The regression includes time fixed effects at the year-month level ($Month_t$) and regional fixed effects at the 1 x 1 kilometer-grid level ($Grid_j$). This method allows for controlling effects that are constant over time for each grid and consistent across grids. The fixed effects notably capture time-invariant neighborhood characteristics. Together with the extensive list of control variables, this approach aims to isolate the impact of noise reduction by the RNPA.

I conduct several robustness checks to corroborate the baseline findings. Firstly, I narrow the sample to observations within a 3 km proximity to the tracks. The control group in this case consists of all residences at or above the 500 m threshold and up to 3 km. Such a framework would improve the similarity between the treatment and control groups by identifying a closer neighborhood. The baseline specification allows for larger distances, even up to the municipal boundary. Second, I eliminate the 15 biggest cities with approximately 500,000 residents from the sample. Next, I remove cities with at least 100,000 inhabitants from the sample. The objective of utilizing various regional samples is to avoid agglomeration areas from dictating the estimated effects in the baseline specification, given housing costs are usually higher in such regions. In the next robustness check, a neutral zone will be established through the omission of all observations within a distance range of 500 m to 1,000 m avoiding potential spatial spillovers at the treated threshold. The effects are expected to be larger than the baseline as the treatment and control groups are more distinct in this setting.

The second set of robustness checks employs alternative regional fixed effects by integrating zip-code regional fixed effects instead of grid-level fixed effects. Additionally, I incorporate a state-time trend to mitigate state-specific time effects. A critical assumption for conducting this kind of analysis is that both the control and treatment groups experience parallel evolution before the treatment (July 2017). To ensure this assumption, I conduct a pre-trend analysis. I divided the pre-treatment period into four periods lasting approximately 12 months each and reapplied the baseline regression equation.[7] The analysis, together with Figure 1.4 displaying the temporal evolution of house prices in graphical form, provides verification that the pre-trend assumption holds. Next, I conduct a placebo regression by restricting the sample to the control period before July 2017, and the treatment time is moved to the middle of the control period, which begins in July 2015 for this setting. This assumes that half of the observation period is under treatment. The effect is projected to be insignificant due to the RNPA being implemented in 2017; thus, there is no treatment yet.

I also implement additional robustness checks in the appendix. All main railroads, instead of just freight train corridors, are utilized to demonstrate that the RNPA operates as intended and decreases noise levels in the transportation sector. When mixed-used tracks and non-transportation are added, the observed effect is expected to be more obscured and smaller (see Section 1.B of the appendix). I also use a leave-one-out estimation, excluding each of the six freight train corridors once to eliminate the possibility of

[7]The period $t-4$ comprises one additional month (compared to $t-1$ to $t-3$) due to the odd total number of months in the control period.

a specific set of tracks driving the findings (refer to Section 1.C of the appendix). Additionally, I add the distance to noise barriers as an extra control variable to the model. One potential concern is that the RNPA's impact may get confused with other countermeasures against high noise levels. This test aims to eliminate the impact of any barriers (refer to Section 1.D of the appendix).

1.3.2 Data and Descriptive Statistics

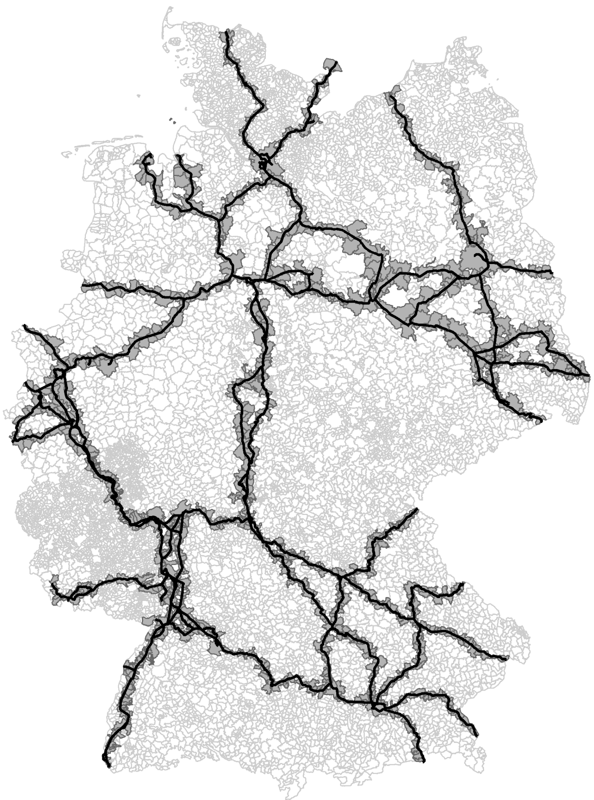
The study combines multiple data sources to create an extensive set of covariates directly controlling for important factors influencing house prices. For the housing data, I rely on the RWI-GEO-RED data set for house sales, which is based on data provided by the online platform ImmobilienScout24.de (RWI, 2021). The data set encompasses all sale listings on the website which are for residential use, on a monthly basis and within the period of 2007 to 2021. The analysis is centered on the time frame from June 2013 to June 2021, providing a balanced span of data that covers four years before and after the RNPA was enacted.

The data set has several advantages. Firstly, it is highly disaggregated at the unit level, permitting the identification of the exact geographical location to determine the proximity between the homes and the railroad tracks. Secondly, the data set contains a substantial number of housing units (with approximately 1.1 million included in the estimation sample), thereby allowing for robustness checks and heterogeneity analyses based on subgroups, without concerns for sample size. The data set provides a comprehensive list of specific features relating to the houses, all of which are incorporated in X_{ij}. These features comprise the living area, number of rooms, number of bathrooms, heating system, as well as the age and condition of the building.[8] The price listed in the data set reflects the price advertised and may differ from the actual transaction price, which is not observable in such great detail. More information on the data and variables utilized can be found in Schaffner (2020).

[8]To ensure representativeness, I exclude homes featuring implausible values that do not reflect typical dwellings, eliminating those falling below the 1^{st} and above the 99^{th} percentiles. For example, homes sold above 1.9 million Euros or have more living space than 480 square meters are dropped.

There are six freight corridors dedicated to rail transport of goods in Germany with the goal of linking major industrial centers throughout Europe.[9] The detailed routes of each corridor were obtained from the map service provided by the European Commission (2021). The tracks are geographically referenced using Geographic Information System (GIS) tools to make them usable for statistical analysis. Figure 1.3 displays the included tracks. Almost all states (except Thuringia) record at least some traffic on these corridors. It highlights the broad geographical coverage as a unique feature of this study.

Figure 1.3: Freight Train Corridors and Covered Municipalities



Notes: The figure shows the course of the covered railroad tracks of freight train corridors in Germany (in black). It also highlights the municipalities crossed by these tracks (in dark grey), which form the treatment and control groups.
Source: Author's graph. The railroad track information is provided by European Commission (2021). The administrative boundaries of states and municipalities are based on Federal Agency for Cartography and Geodesy (2019).

[9] These are the Rhine-Alpine, North Sea-Baltic, ScanMed, Atlantic, Orient/East-Med, and Rhine-Danube corridors.

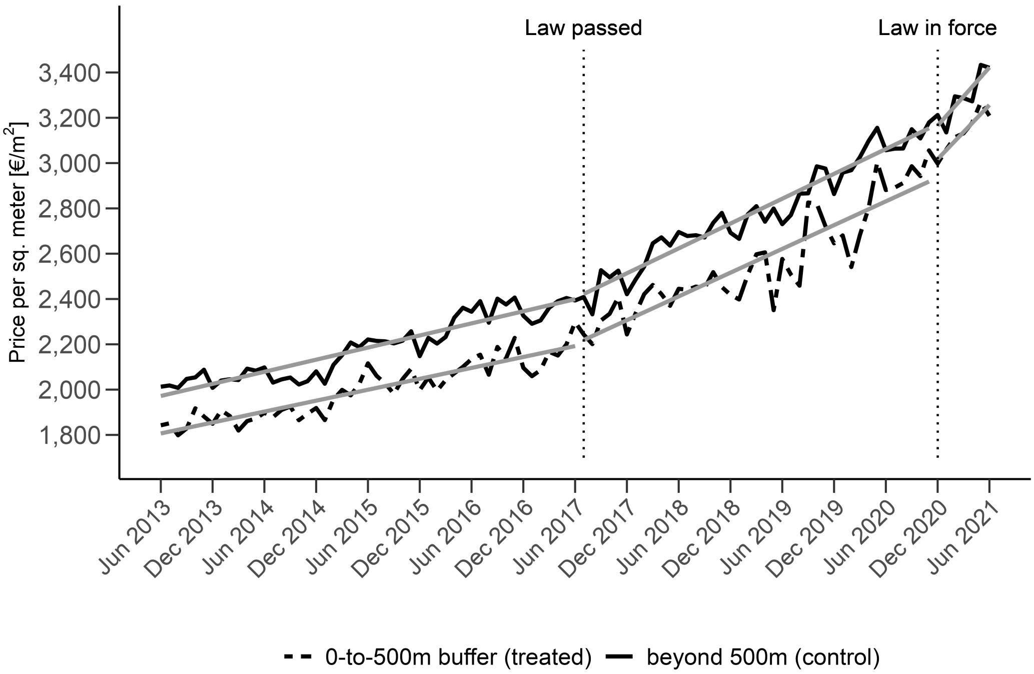
Using the housing data and railroad corridors, I compute Euclidean distances (straight-line distances) between residences and tracks to identify areas impacted by proximity to the railroad tracks. In the baseline setting, the buffer is denoted by the dummy variable *Buffer500* with a value of one assigned to homes within 500 m of the tracks, indicating exposure to the railroad-generated noise. Observations exceeding this threshold form the control group. To ensure the geographical proximity of both groups, the maximum distance to the tracks is restricted by the municipal border, as illustrated in Figure 1.3. The shaded areas highlight the included municipalities and the distance constraint. In the heterogeneity analysis (refer to Section 1.4.3), the distance buffer is increased. Instead of utilizing a sole distance buffer, various distance indicators are utilized to define the treated observations, including 50 m, 100 m, 250 m, 500 m, 750 m, and 1,000 m.[10]

One key assumption for the identification strategy is that the treatment and control groups experience the same trend over time. To verify this, I present visual evidence in Figure 1.4, depicting the evolution of house prices (measured in price per square meter) over time for homes located within 500 m from the tracks (dashed line) and those situated further away (solid line) in the baseline setting. Notably, both groups exhibit a similar trend as demonstrated by the grey solid lines. Especially prior to the adoption of the RNPA (July 2017), housing prices followed a similar trend in both groups, suggesting a shared trend assumption. Nevertheless, properties situated within 500 meters of tracks exhibited poorer performance in price over the entire observation period, thereby emphasizing the disamenities these neighborhoods are confronted with.

Since location has a significant impact on home prices (see, for example, Kiel and Zabel, 2008), I add the straight-line (Euclidean) distances to the nearest regional centers of different sizes (large, medium, or small) as control variables. The data originates from the Federal Office for Building and Planning (BBSR) (2020a). The most recent information available, from 2017, is utilized. The BBSR calculates distances between municipalities and defines centers of importance based on an accessibility model. These

[10]The 1,000 m threshold represents the 40^{th} percentile when calculating the distance between homes and the nearest railroad track. This leads to approximately twice the number of observations being subjected to railroad noise in comparison to the baseline 500 m buffer specification, i.e., up to the 20^{th} percentile.

Figure 1.4: House Prices over Time



Notes: The figure shows the evolution of house prices (as price per square meter) for the treated group (distance to tracks 0 to 500 m) given by the dashed line, and for the control group (distance larger than 500 m) given by the solid line. The RNPA implementation process is indicated by vertical lines, with July 2017 marking the law's passing and December 2020 representing the law coming into effect. The solid grey lines indicate the trend of prices for the respective group during the implementation process of the law.
Source: Author's graph. The housing data is provided by RWI (2021).

centers provide cultural, medical, and general lifestyle services, and are significant employment locations. The BBSR distinguishes between small, medium, and large centers, which differ in the services they supply.[11] In total, the BBSR lists 152 large, 956 medium, and 2,488 small regional centers. Regional centers are included to account for the effects of commuting and the interdependence between regions and municipalities. These distances provide a direct means of accounting for location effects.

Since trains are not the sole noise source to impact house prices, I also

[11] Large regional centers, for example, have a comprehensive health system with general doctors and specialists. They also typically host the region's administrative infrastructure. Medium centers also cover the basic services but, for instance, lack specialists (Einig, 2015). Additionally, both types represent central workplaces, which make them major commuting locations. Small regional centers cover basic needs; hence, they are an important factor in regional infrastructure, particularly in more remote areas.

add distances to three other primary noise sources - airports, industrial plants, and main streets - to isolate the railroad noise effect. The data originates from the European Union (EU) directive for noise mapping, defining primary noise sources in Germany (see EU, 2002) and is provided by the Federal Environmental Agency (UBA, 2019a), which offers geographically referenced airport noise maps for 2017. I calculate the distance to airports, including major airports, registering at least 50,000 starts and landings annually.[12] I further add airports in metropolitan areas with a population of at least 100,000 citizens, which are not already defined as major airports (UBA, 2019b).[13] For industrial plants, the EU directive for noise mapping identifies central industrial sites in metropolitan areas (UBA, 2019c), which are also added to the analysis by calculating the distance between houses and the closest industrial plant. To control for the proximity to streets, I use information by the UBA (2019d) regarding the geographical location of main streets in Germany in 2017. These streets reportedly have a traffic volume of at least 3 million cars annually.

Living near railroad tracks not only exposes residential areas to increased noise levels but also provides easier access to transportation. Therefore, I control for the Euclidean distances between homes and train stations and between houses and highway ramps. DB Station and Service AG (2020) provides a list of the geographical locations of all public train stations in Germany. As Voith (1993) noted, access to highways is critical in estimating house prices. Therefore, highway ramps are collected by Open Street Map data using the tag *highway:junction*. Both accessibility variables refer to entry points to the traffic infrastructure network. The impact of these variables on house prices could be positive or negative. For instance, Debrezion et al. (2011) find a negative effect of the distance to train stations on house prices, while Allen et al. (2015) discover that greater distances to the next highway ramp are associated with price decreases. Levkovich et al. (2016) evaluates the positive value of accessibility and the negative impact of noise and traffic intensity. It is important to control for these accessibility factors as they can act as independent noise sources.

[12] Major airports are located in Berlin, Stuttgart, Munich, Nuremberg, Frankfurt am Main, Hamburg, Hannover, Cologne, Düsseldorf, and Leipzig.

[13] These are: Mannheim, Bremen, Mülheim a.d.R., Dortmund, Essen, Mainz, and Dresden.

Table 1.1 provides a summary of all variables and their descriptions. Table 1.2 presents summary statistics for these variables, divided into three periods: the control period (June 2013 to June 2017), the period during which the RNPA was passed and under adoption (July 2017 to November 2020), and the period when the act was fully in place and non-compliance could be fined (December 2020 to June 2021). The summary statistics differentiate houses within 500 m of the tracks (noise-treated) from those further away (control group) for each period separately.

Table 1.1: Description of the Utilized Variables

Variable	Description
A. Housing characteristics	
Log(house price)	Logarithm of the listing price for housing units
Price	Listing price for housing unit (in Euro)
Number of rooms	Total number of rooms
Age	Age of the building
Number of floors	Total number of floors
Endowment	Classification of the endowment of the house
Number of bathrooms	Total number of bathrooms
Plot area	Size of the property area (in m^2)
Heating	Classification of the heating system
Under construction	Indicator for the house being under construction (= 1) or not (= 0)
Living space	Size of the living space (in m^2)
Condition	Classification of the condition of the house
B. Regional factors	
Dist. large regional center	Straight-line distance to nearest large regional center (in km)
Dist. medium regional center	Straight-line distance to nearest medium regional center (in km)
Dist. small regional center	Straight-line distance to nearest small regional center (in km)
C. Additional noise sources	
Dist. airport	Straight-line distance to the nearest airport (in km)
Dist. industrial plant	Straight-line distance to the nearest industry site (in km)
Dist. main street	Straight-line distance to the nearest street (in km)
D. Accessibility	
Dist. highway ramp	Straight-line distance to the nearest highway ramp (in km)
Dist. train station	Straight-line distance to the nearest train station (in km)

Notes: The table summarizes all variables used in the analysis. Endowment ranges from simple to deluxe, allowing for four categories in total. Heating describes the power source and includes types like electric heating and gas or oil heating. 13 categories are available in the data set. The condition of the house can vary from first occupancy to dilapidated. The variable combines ten categories. More details are listed in Schaffner (2020).
Source: Author's table.

Table 1.2 shows that houses located within 500 m of the tracks sell for a lower price, on average, at any given time. However, after the introduction of the RNPA, houses within 500 m of the tracks caught up to the prices of their counterparts in the control group. Prior to the enactment of the RNPA (before July 2017), houses within 500 m of the tracks sold for an average of approximately 34,000 Euros less than their counterparts in the control group. During the adoption period, this deviation reduces to approximately 30,000 Euros and to 21,000 Euros after the RNPA is fully enforced. Although the noise-exposed houses still sell for less than the unexposed ones, an exploratory comparison shows a gain of approximately 13,000 Euros in listing prices (or around 2.6% of the price of the treated) when the noise-reducing law is fully implemented. Similarly, when considering the unconditional difference-in-difference estimates (see columns (7) and (9) of Table 1.2), the houses that were treated and located within 500 m of the tracks gained value after the implementation of the RNPA. In fact, these differences amount to around 3,800 Euros (or 0.8%) during the adoption of the RNPA (July 2017 to November 2020) and around 12,400 Euros (or 2.4%) when the law was fully enrolled.

Table 1.2 also shows some differences in housing unit characteristics between the treatment and control groups. For instance, treated houses have a higher average age and a smaller plot area. As anticipated, homes within 500 m of the tracks are also closer to the next train station. Therefore, these homes have an advantage in accessing railroad services, which could increase their appeal compared to other homes, reassuring the inclusion of the distance to train stations as a covariate.

Regarding other data sources in the heterogeneity analysis (see Section 1.4.3), I study the effectiveness of the RNPA for various degrees of urbanization. I use settlement density to define more or less densely populated neighborhoods. The data, provided by BBSR (2020b) for 2017, describes the number of people per square kilometer of residential and traffic areas and ranges from 0 to 6,263 people per square kilometer. The settlement density is divided into quartiles to form subsets, which are then used to categorize municipalities as highly sparse, sparse, dense, or highly dense.

Table 1.2: Summary Statistics of the Housing Data

	Before RNPA (< July 2017)		RNPA passed ($\geq$ July 2017)		RNPA in force ($\geq$ December 2020)		uncond. DiD RNPA passed		uncond. DiD RNPA in force	
	Dist. to tracks $\leq$ 500m	Dist. to tracks > 500m	Dist. to tracks $\leq$ 500m	Dist. to tracks > 500m	Dist. to tracks $\leq$ 500m	Dist. to tracks > 500m	$[(3)-(1)]-[(4)-(2)]$	SE of (7)	$[(5)-(1)]-[(6)-(2)]$	SE of (9)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. Housing characteristics										
Log(house price)	12.491	12.582	12.729	12.801	12.959	12.988	0.019	0.003	0.063	0.006
Price	319,411.802	353,151.45	408,391.582	438,314.815	497,718.028	519,061.428	3,816.415	1,237.59	12,396.248	3,059.031
Number of rooms	5.959	5.771	5.871	5.646	5.802	5.61	0.037	0.012	0.003	0.025
Age	50.991	47.649	53.916	50.989	69.474	65.431	-0.416	0.172	0.70	0.407
Number of floors	1.652	1.62	1.645	1.614	1.691	1.645	-0.002	0.004	0.014	0.009
Endowment	2.267	2.303	2.342	2.367	2.421	2.412	0.011	0.003	0.045	0.006
Number of bathrooms	1.496	1.498	1.536	1.517	1.583	1.548	0.020	0.004	0.037	0.01
Plot area	590.971	631.284	596.546	629.354	596.648	621.72	7.507	2.096	15.242	4.50
Heating	11.643	11.579	10.825	10.782	10.87	10.761	-0.021	0.016	0.045	0.036
Under construction	0.012	0.012	0.011	0.013	0.009	0.01	-0.002	0.001	-0.001	0.001
Living space	166.211	166.049	166.62	164.001	165.559	162.356	2.457	0.325	3.041	0.682
Condition	5.637	5.562	5.573	5.506	5.695	5.633	-0.008	0.012	-0.013	0.026
B. Regional factors										
Dist. large regional center	15.246	14.137	15.921	14.786	16.656	15.308	0.027	0.056	0.24	0.13
Dist. medium regional center	6.732	7.141	6.801	7.492	6.981	7.87	-0.283	0.026	-0.48	0.058
Dist. small regional center	9.82	15.3	10.131	14.881	10.621	14.313	0.73	0.082	1.788	0.177
C. Additional noise sources										
Dist. airport	34.885	31.171	38.406	35.541	37.217	37.506	-0.848	0.165	-4.002	0.352
Dist. industrial plant	18.959	15.421	19	16.113	20.109	17.307	-0.651	0.106	-0.736	0.235
Dist. street	1.066	1.227	1.136	1.311	1.135	1.382	-0.015	0.009	-0.086	0.021
D. Accessibility										
Dist. highway ramp	3.603	3.594	3.793	3.837	3.967	4.125	-0.053	0.022	-0.168	0.053
Dist. train station	1.545	2.746	1.51	2.814	1.492	2.879	-0.103	0.008	-0.186	0.017
Observations	141,087	552,114	78,060	314,436	11,669	45,609	1,085,697		750,479	

Notes: The table lists summary statistics for the included variables. Mean values are shown for houses within 500 m of railroad tracks (treatment group) and houses beyond this threshold (control group) for the periods before the RNPA was implemented (June 2013 to June 2017), after it was passed (July 2017 to November 2020) and when it was fully adopted (December 2020 to June 2021). The columns (7) and (9) show the unconditional difference-in-differences (DiD) for periods of the RNPA being passed and being in force. Columns (8) and (10) show the respective robust standard errors.
Source: Author's table.

1.4 Results

1.4.1 Main Results

Table 1.3 column (1) displays the coefficients of interest and the basic noise effect (γ) obtained from estimating Equation (1.1). Both interaction terms are positive and highly significant.[14] The interaction between the variables *LawPassed* and the treatment ring *Buffer500* indicates that houses located within 500 m of tracks experienced an average price increase of 0.5% compared to those located further away.[15] This effect is even more pronounced after the law was fully implemented, as the adoption effect during the initial period is much smaller than the actual treatment effect of the RNPA. This seems reasonable, as modernization was still an ongoing process during the period of adoption. Noise levels may be only marginally lower than before the RNPA, depending on the number of already upgraded freight trains at the time. Taking both interactions together, the value gains outweigh the overall negative noise effect of 2%.

1.4.2 Robustness Checks

Table 1.3 (columns 2 through 5) shows the results of the first set of robustness checks. Restricting the control group to three kilometers from the tracks and making the control and treatment groups more similar[16] reduces the sample by about 300,000 units compared to the baseline setting (see column (1) of Table 1.3). However, the results regarding the impact of the RNPA on house prices are not much different from the baseline results.

Column (3) shows the results without the 15 largest cities with at least

[14] I show the full regression output with all control variables and the effects of interests in Section 1.A of the appendix.

[15] I interpret the reduced form estimates directly as percent change as the estimated effects are relatively small. The precise interpretation using the formula $(e^{\beta} - 1) \times 100\%$ leads to a percent change of 2.53% for *LawInForce* × *Buffer500*.

[16] in terms of summary statistics

Table 1.3: Baseline Results and Robustness Checks I

Dependent Variable:	log(house price)				
	Baseline	Restr. 3km	Excl. 500k	Excl. 100k	Excl. NZ
	(1)	(2)	(3)	(4)	(5)
Buffer500	-0.020^{***}				
	(0.002)				
LawPassed × Buffer500	0.005^{***}	0.005^{***}	0.011^{***}	0.008^{***}	0.007^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
LawInForce × Buffer500	0.025^{***}	0.030^{***}	0.028^{***}	0.021^{***}	0.026^{***}
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Full set of controls	✓	✓	✓	✓	✓
Sample restricted		✓	✓	✓	✓
Fixed-effects					
Month FE	✓	✓	✓	✓	✓
Grid FE	✓	✓	✓	✓	✓
Fit statistics					
Observations	1,142,975	866,856	914,268	709,781	955,461
R^2	0.82050	0.81381	0.80516	0.80528	0.82648
Within R^2	0.51012	0.51302	0.51430	0.51108	0.50963

Notes: The table shows the results for the baseline specification and the first set of robustness checks. *Buffer500* indicates houses within 500 m of the tracks (treated). *LawPassed* is equal to one for periods between July 2017 and November 2020, and *LawInForce* represents the periods December 2020 to June 2021. Both variables represent the implementation process of the RNPA. Column (1) shows the results for the baseline specification. Column (2) restricts the observations to 3km from the tracks. Column (3) excludes the 15 largest cities with a population of approximately 500,000 residents. Column (4) drops all large cities with at least 100,000 residents. Column (5) defines a neutral zone and excludes houses between 500m and 1,000m. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

500,000 citizens.[17] Both effects of interest increase compared to the baseline results. The adoption period effect rises to 1.1%, and the actual treatment effect increases to 2.8%. A comparable observation can be made when excluding specific regions to a greater extent. If all cities with more than 100,000 residents are eliminated, the number of observations decreases by approximately 400,000 (see column (4) Table 1.3). The estimated coefficients

[17]These cities are: Berlin, Hamburg, Munich, Cologne, Frankfurt am Main, Stuttgart, Dusseldorf, Leipzig, Dortmund, Essen, Bremen, Dresden, Hannover, Nuremberg, and Duisburg. All of the cities have a population of approximately 500,000 citizens, with the exception of Duisburg, which has a slightly smaller population (Federal Office of Statistics, 2021b).

change to 0.8% during the adoption period and 2.1% after the RNPA was ultimately implemented.

By eliminating these metropolitan areas, I aim to exclude potential confounding factors. Assuming that large cities have a higher overall noise level due to their size, complex traffic infrastructure, and higher building densities, the RNPA's impact would be diminished as it would be harder to identify changes in the noise level of a particular source, such as railroad noise. However, cities are also focal points of economic and social activities, making them attractive for living and working. As a result, the cost of living and housing prices are generally higher. Table 1.3 hints at larger effects when metropolitan areas are removed (except in column (4) for the actual treatment period). This aligns with the expectation that improvements are more recognizable in rather remote areas. Despite the changes in effect size, removing agglomeration areas does not change the direction or significance of the results. Large cities do not seem to drive the overall results.

Column (5) of Table 1.3 displays the results when excluding homes between 500 m and 1,000 m from the estimation. The intention is to separate the control and treatment groups clearly from each other by introducing the neutral zone, eliminating spatial spillovers. The results turn out to be slightly larger than in the baseline model. The minor differences in effect size do not suggest large spillover effects between the treated and the control group.

Table 1.4 shows the second set of robustness checks results. Using zip-code rather than grid-level fixed effects reduces the coefficient size to 0.4% and 1.7%, on average, compared to the baseline results. The effects are still significant at the 1% level. Column (3) shows the results when a state-specific time trend is added to Equation (1.1). Again, this addition changes neither significance nor direction. However, it impacts the effect size, which increases for both interaction terms. After the law was passed, units within 500 meters increased in value by 1.5% relative to houses above the threshold. The effect is even more prominent after December 2020. Column (4) checks for the pre-trend assumption. By splitting the control periods (prior to July 2017) into four time slots, the test analyzes whether the control and treatment groups behaved similarly before the law was adopted. Note that July 2017 is the reference point in time (= t) in this setting. The periods under treatment are defined similarly to the previous models, with $t+1$ being $LawPassed$ and $t+2$ representing $LawInForce$. As expected, the pre-treatment periods show no significant effect. After the RNPA was implemented, similar effect sizes as before are observed (1.1% to 3.0%). This particularly supports the baseline results because it hints at the same trend for the treatment and control groups.

For the final robustness check, the observation period is restricted to before July 2017, and the treatment is assumed to start in July 2015. The variable *Placebo* equals one for the months between July 2015 and June 2017, meaning that half of the period is under treatment. As expected, the treatment effect turns out to be insignificant since there is no treatment administered through the RNPA, yet.

1.4.3 Heterogeneity Analysis

Differences in Treatment Intensity

For the initial heterogeneity test, I examine the impact of noise reduction at varying treatment intensities, specifically at different distances from the railroad tracks. The baseline model defines the treatment as a distance buffer of 500 m. This heterogeneity scenario defines six buffers ranging from 50 m to 1,000 m, with each buffer indicating whether the listed house is within the respective distance. The control group in this setting consists of houses located beyond 1,000 m and up to the municipality border.

In general, houses located closer to train tracks are exposed to higher levels of noise caused by passing freight trains. It is expected that the greater the distance between the tracks and the house, the smaller the impact of the law-induced noise reduction. The results (Figure 1.5) confirm the aforementioned expectation as the shortest distance (50 m) also shows the largest coefficients (4.9% to 5.5%). The adjacent buffer of 100 m displays the second-highest effects. The coefficients are substantially larger than the baseline results, particularly at the shortest distance. Overall, the effect magnitude decreases with distance, as expected. However, the results for a distance of 500 m disrupt the pattern of decreasing effect sizes with distances. While the effect for the actual treatment period is similar to at 100 m, the effect for the adoption period is insignificant.

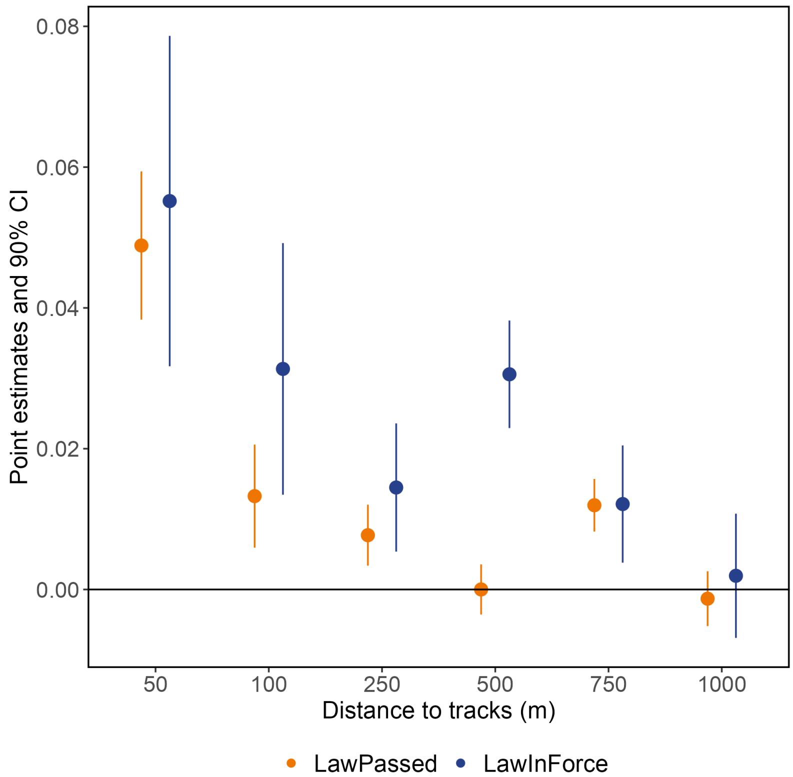
Table 1.4: Robustness Checks II: Zip-code FE, Time Trend, Pre-Trends, and Placebo Regression

Dependent Variable:	log(house price)				
	Baseline	Zip-code FE	Time trend	Pre-trends	Placebo
	(1)	(2)	(3)	(4)	(5)
LawPassed × Buffer500	0.005***	0.004***	0.015***		
	(0.002)	(0.002)	(0.002)		
LawInForce × Buffer500	0.025***	0.017***	0.037***		
	(0.003)	(0.004)	(0.003)		
Periods_{t-4} × Buffer500				0.004	
				(0.006)	
Periods_{t-3} × Buffer500				0.008	
				(0.007)	
Periods_{t-2} × Buffer500				0.011	
				(0.007)	
Periods_{t-1} × Buffer500				−0.000	
				(0.007)	
Periods_{t+1} × Buffer500				0.011*	
				(0.006)	
Periods_{t+2} × Buffer500				0.030***	
				(0.007)	
Placebo × Buffer500					−0.001
					(0.002)
Full set of controls	✓	✓	✓	✓	✓
State time trend			✓		
Sample restricted					✓
Fixed-effects					
Month FE	✓	✓	✓	✓	✓
Grid FE	✓		✓	✓	✓
Zip-code FE		✓			
Fit statistics					
Observations	1,142,975	1,142,972	1,142,975	1,142,975	693,201
R^2	0.82050	0.77271	0.82323	0.82050	0.82628
Within R^2	0.51012	0.51032	0.51757	0.51013	0.52890

Notes: The table shows the results for the second set of robustness checks. *Buffer500* indicates houses within 500 m of the tracks (treated). *LawPassed* is equal to one for periods between July 2017 and November 2020, and *LawInForce* represents the periods December 2020 to June 2021. Both variables represent the implementation process of the RNPA. Column (1) restates the baseline findings (for comparison). Column (2) adopts zip-code regional fixed effects. Column (3) adds a state-specific time trend. Column (4) displays the results for the pre-trend analysis with the division of the control period into four time intervals. Column (5) shows the results of limiting the sample to the control period and assuming the treatment to start in July 2015 (placebo test). Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

Interestingly, there is no effect for the furthest distance (1,000 m).[18] This finding suggests that RNPA impacts house prices up to a certain point, which is also reasonable as changes in noise levels are mitigated by distance.

Figure 1.5: Heterogeneity Analysis: Treatment Intensity



Notes: The figure shows the point estimates (dots) and 90% confidence interval (CI) [vertical lines] for the extension of the model by defining six treatment buffers in the range from 50 m to 1,000 m (instead of only 500 m as in the baseline setting). Orange estimates represent the interaction between *LawPassed* (i.e., adoption period) and the different distances. Blue estimates represent the interaction between *LawInForce* (i.e., actual treatment period) and the different distances.
Source: Author's graph.

[18]This finding also holds up when I apply robustness checks like excluding cities with 500,000 or 100,000 residents from the sample restating the "natural" threshold up to which the RNPA seems to be effective.

Differences in Urbanization

I study the impact of the RNPA under various degrees of urbanization using information on settlement density.[19]

Table 1.5: Heterogeneity Analysis: Urbanization

Dependent Variable:	log(house price)				
	Baseline	Highly sparse	Sparse	Dense	Highly dense
	(1)	(2)	(3)	(4)	(5)
LawPassed × Buffer500	0.005***	−0.001	0.013***	0.024***	−0.004
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
LawInForce × Buffer500	0.025***	0.018**	0.023***	0.042***	0.005
	(0.003)	(0.007)	(0.007)	(0.006)	(0.007)
Full set of controls	✓	✓	✓	✓	✓
Fixed-effects					
Month FE	✓	✓	✓	✓	✓
Grid FE	✓	✓	✓	✓	✓
Fit statistics					
Observations	1,142,975	285,061	284,441	284,246	289,081
R^2	0.82050	0.78319	0.77150	0.79076	0.80327
Within R^2	0.51012	0.45418	0.53862	0.55514	0.53055

Notes: The table shows the regression output for subsamples of settlement densities. *Buffer500* indicates houses within 500 m of the tracks (treated). *LawPassed* is equal to one for periods between July 2017 and November 2020, and *LawInForce* represents the periods December 2020 to June 2021. Both variables represent the implementation process of the RNPA. Column (1) restates the baseline results (for comparison). Column (2) represents highly sparse, column (3) sparse, column (4) dense, and column (5) highly dense municipalities. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

Table 1.5 indicates that municipalities with high levels of sparsity exhibit mixed results. Although the effect of the adoption period is not significant, the effect of the RNPA being fully adopted increases house prices by an average of 1.8%. The coefficients for the sparse type are both significant and have similar sizes to previous results. The RNPA has a much larger impact on densely populated areas than in the baseline setting. The adoption effect is 2.4%, and the following period shows an increase to 4.2%. The estimates

[19] The variable is divided into groups based on the quartiles of the settlement density and thus, ranging from highly sparse to highly dense regions (see also Section 1.3.2).

for the highly-dense types do not show any significance. This could be due to the higher intensity of noise sources in these areas. They tend to have a higher share of business activity, traffic volume, commuting, and population density, resulting in less quiet places and overall higher environmental noise levels. It is possible that changes in noise from one source, such as freight train transport, may be less noticeable. This finding will be studied in greater detail in the following heterogeneity specifications.

Differences in Other Noise Sources

The preceding paragraphs indicated that the positive effects of the RNPA do not manifest in densely populated areas. This section examines the effect of RNPA on neighborhoods that are burdened by noise due to their proximity to other noise sources. The analysis is based on the abundance of data available. The distances between the housing units and the noise sources form the basis for identifying regions affected by high levels of environmental noise and disamenities from these locations (see Section 1.3.2 for the description of the single sources). I apply a data-driven approach to define the samples based on the first and second quartiles of the distances. (see Table 1.6).

Table 1.6: Distances to Other Noise Sources

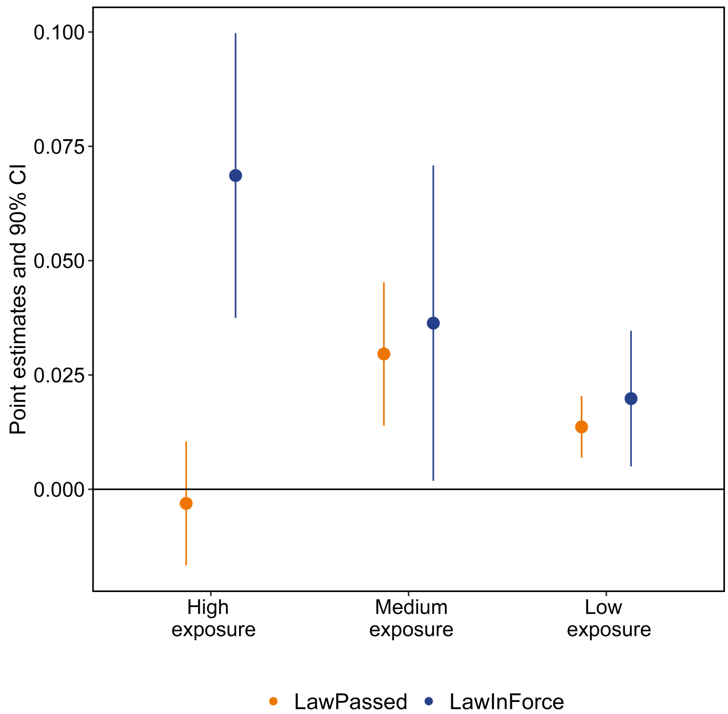
Noise source	1^{st} quartile	2^{nd} quartile
	(1)	(2)
Airports	8.8 km	20.4 km
Industrial plants	3.2 km	9.0 km
Main streets	0.2 km	0.6 km

Notes: The table displays the distances to other noise sources (airports, industrial plants, and main streets) in kilometers for the first and second quartiles. The noise source information is given by UBA (2019a,b,c,d).
Source: Author's table.

Highly Exposed Locations

First, I study the combination of all three noise sources (airports, industrial plants, and main streets) to identify locations with high overall noise levels. The highly exposed locations are within the first quartile of each of the different sources. The medium exposure group ranges between the first and second quartile in terms of distance. Finally, the neighborhoods with lower exposure are farther away than those in the second quartile. Therefore, I assume those are also the quietest places concerning the considered noise sources. The baseline regression is then repeated for each subset. Figure 1.6 shows the results for this exercise with the interaction between the treatment indicator (*Buffer500*) and the adoption period (*LawPassed*) highlighted in orange and the interaction with the actual treatment period (*LawInForce*) displayed in blue.

Figure 1.6: Heterogeneity Analysis: Highly Exposed Locations



Notes: The figure shows the point estimates (dots) and 90% confidence intervals (CI) [vertical lines] based on the combination of all three major noise sources (airports, industrial plants, and main streets). Highly exposed neighborhoods rank within the first quartile of distance to all noise sources. Medium-exposure regions lie within the first and second quartile, and low-exposure locations are beyond the second quartile in terms of distance. The orange color represents the interaction between the treated indicator (*Buffer500*) and the adoption period (*LawPassed*). The blue tone shows the results for the interaction with the actual treatment period (*LawInForce*).
Source: Author's graph.

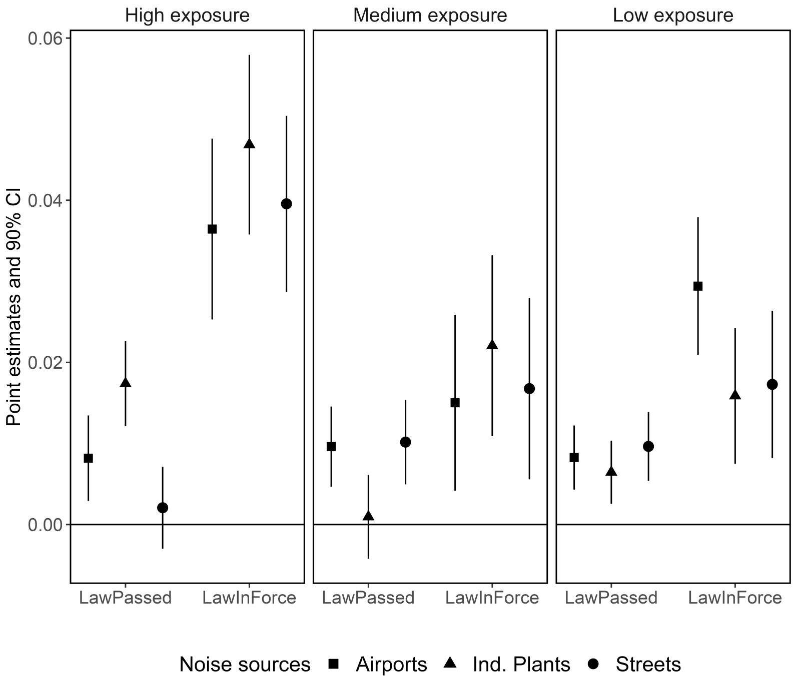
The results reveal that the high-exposure group gained the most from implementing the RNPA, at least for the actual treatment period (after December 2020). The point estimates amount to 6.9%, which is substantially larger than any previous effects. The effect for the adoption period is insignificant, indicating that the noise changes in the railroad sector are likely not strong enough to appear in the point estimate for these noisy places. The coefficients for the medium-exposed group are lower than for the first group but still larger than in the baseline setting. The smallest impact of the RNPA introduction is attributed to low-exposure locations. So, there is a decline in effect size from highly exposed neighborhoods to low-exposed ones. The results indicate that individuals exposed to higher environmental noise levels benefit the most from noise reduction efforts in a specific sector.

Effects by Distance and Source

The second analysis of heterogeneity regarding noise sources takes the first exercise one step further by analyzing the individual effects of each noise source. The three-group definition from the previous setting (high, medium, and low exposure) is used again, but each noise source is treated separately.

Analyzing these noise source-specific patterns and using the three exposure groups reveals similar patterns as before (see Figure 1.7). The impact during the adoption period is smaller compared to the months when the RNPA is fully enrolled. The effect sizes are also quite stable across noise source and exposure groups. The results are more versatile for the actual treatment period after December 2020. The high exposure group, i.e., locations in the immediate surroundings of the respective noise source, also show the strongest reaction to the final introduction of the RNPA. Therefore, the previous results are confirmed in this analysis. The finding that those who live under the highest noise levels near airports, industrial plants, or streets also experience the largest increases in house prices is unexpected but supports the findings when all noise sources are studied in combination. It also corresponds to the heterogeneity analysis of the closest homes to the tracks, where the highly exposed houses (i.e., those in immediate proximity to the tracks) also gained the most from the introduction of the RNPA. The medium-exposure and low-exposure regions do not vastly differ in their effect sizes.

Figure 1.7: Heterogeneity Analysis: Effects by Distance and Noise Source



Notes: The figure shows the point estimates (symbols) and 90% confidence intervals (CI) [vertical lines] for high, medium, and low exposure locations by the respective noise source (airports, industrial plants, and main streets). Highly exposed neighborhoods rank within the first quartile of distance to the respective noise source. Medium-exposure regions lie within the first and second quartile, and low-exposure locations are beyond the second quartile in terms of distance. *Squares* refer to airports as the noise source. *Triangles* indicate industrial plants and streets are displayed by *dots*. The columns *LawPassed* refer to the interaction with the adoption period while *LawInForce* represents the actual treatment period.
Source: Author's graph.

1.5 Conclusion

As noise poses health risks and creates overall disturbance, this chapter assesses the impact of decreased railroad-related noise through a hedonic pricing model. Utilizing variation in noise levels resulting from the RNPA, a law that banned loud freight trains starting in 2017, I study house sales near railroad tracks to determine price changes following its implementation.

The baseline results suggest an increase of house prices within 500 m to the railroad tracks of 0.5% for the period of the RNPA being passed and an effect of 2.5% afterward. Therefore, on average, houses close to the tracks gained value compared to houses sold further away. Several robustness checks confirmed the findings. Especially, the pre-trend analysis, which focuses on the pre-treatment periods (i.e., before July 2017), strengthens the conclusions.

The impact of the RNPA was also studied across various subsets to elaborate on heterogeneous treatment effects. The strongest responses were observed in homes located in the immediate vicinity of the railroad tracks, which is not surprising given their high exposure levels. Therefore, noise reductions should be most beneficial for these households. However, the study of settlement density as a measure of urbanization resulted in mixed outcomes. Studying the effect of RNPA in noisy environments indicates that those with high overall noise levels from various sources - not solely railroads - benefit the most from implementing RNPA.

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Appendix

1.A Full Baseline Results Table

Table 1.A.1: Full Baseline Results

Dependent Variable:	log(house price)
	(1)
A. Housing characteristics	
Under construction	0.008***
	(0.002)
Age	−0.004***
	(0.000)
Age^2	0.000***
	(0.000)
Living space	0.006***
	(0.000)
Living $space^2$	−0.000***
	(0.000)
Plot area	0.001***
	(0.000)
Plot $area^2$	−0.000***
	(0.000)
Number of floors	0.003***
	(0.001)
Number of floors (unknown)	0.003***
	(0.001)
Number of bathrooms	−0.002***
	(0.000)
Number of bathrooms (unknown)	−0.060***

Continued on next page

Table 1.A.1 – *Continued from previous page*

Dependent Variable:	log(house price)
	(1)
	(0.001)
Heating: Electric heating	−0.129***
	(0.006)
Heating: Self-contained central heating	−0.060***
	(0.004)
Heating: District heating	0.005
	(0.005)
Heating: Floor heating	0.046***
	(0.004)
Heating: Gas heating	−0.022***
	(0.004)
Heating: Wood pellet heating	−0.031***
	(0.008)
Heating: Night storage heating	−0.132***
	(0.006)
Heating: Heating by stove	−0.233***
	(0.005)
Heating: Oil heating	−0.037***
	(0.004)
Heating: Solar heating	−0.004
	(0.009)
Heating: Thermal heat pump	0.086***
	(0.004)
Heating: Central heating	−0.024***
	(0.004)
Heating (unknown)	−0.080***
	(0.001)
Endowment: Normal	0.105***
	(0.002)
Endowment: Sophisticated	0.213***
	(0.002)
Endowment: Deluxe	0.321***
	(0.003)
Endowment (unknown)	0.030***
	(0.001)
Number of rooms	−0.006***
	(0.000)

Continued on next page

Table 1.A.1 – *Continued from previous page*

Dependent Variable:	log(house price)
	(1)
Condition: First occupancy after reconstruction	0.053***
	(0.004)
Condition: Like new	0.003**
	(0.001)
Condition: Reconstructed	0.017***
	(0.002)
Condition: Modernized	−0.043***
	(0.001)
Condition: Completely renovated	−0.020***
	(0.002)
Condition: Well-kept	−0.072***
	(0.001)
Condition: Needs renovation	−0.260***
	(0.002)
Condition: By arrangement	−0.145***
	(0.005)
Condition: Dilapidated	−0.538***
	(0.022)
Condition (unknown)	−0.036***
	(0.001)
B. Regional factors	
Distance to large regional center	−0.021***
	(0.002)
Distance to medium regional center	−0.006***
	(0.001)
Distance to small regional center	0.010***
	(0.001)
C. Additional noise sources	
Distance to airports	−0.005***
	(0.001)
Distance to industrial plants	0.016***
	(0.002)
Distance to main streets	0.032***
	(0.002)
D. Accessibility	
Distance to train station	−0.002
	(0.001)

Continued on next page

Table 1.A.1 – *Continued from previous page*

Dependent Variable:	log(house price)
	(1)
Distance to highway ramp	0.006***
	(0.001)
E. Effects of interest	
Buffer500	−0.020***
	(0.002)
LawPassed × Buffer500	0.005***
	(0.002)
LawInForce × Buffer500	0.025***
	(0.003)
Fixed-effects	
Month FE	✓
Grid FE	✓
Fit statistics	
Observations	1,142,975
R^2	0.82050
Within R^2	0.51012

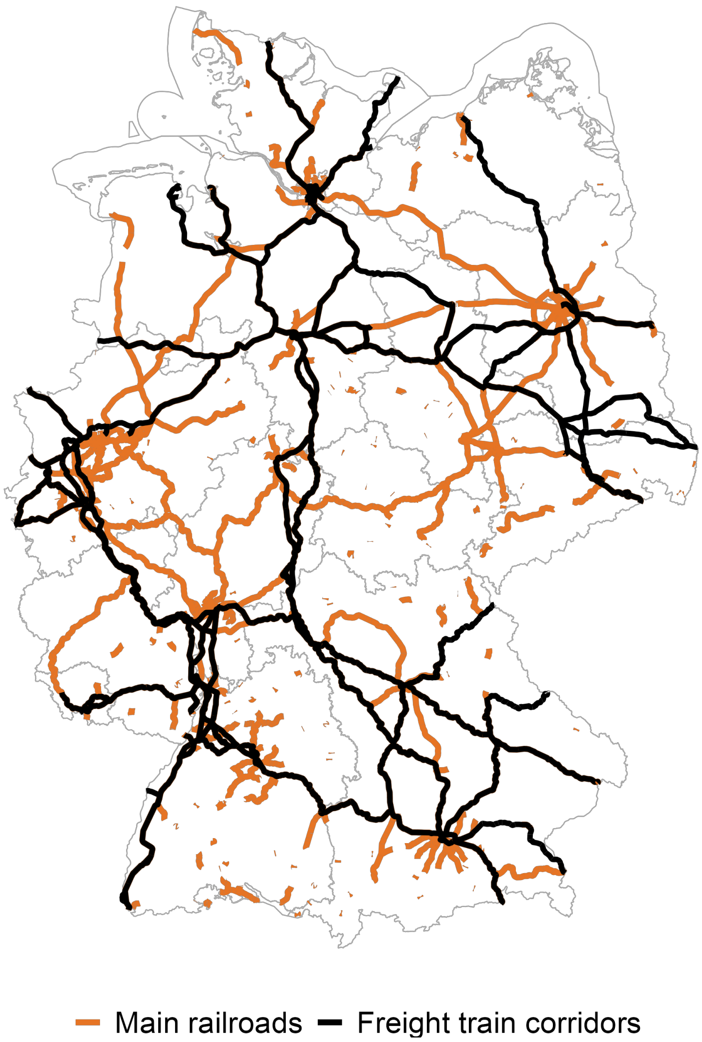
Notes: The table shows the full output table for the baseline specification. An abbreviated version of the table is displayed in Table 1.3. The variables labeled as ”unknown” (e.g., ”Number of floors (unknown)”) are dummy variables that take a value of one if the information is not provided, ensuring that observations with missing data are still included in the analysis. *Buffer500* indicates houses within 500 m of the tracks (treated). *LawPassed* is equal to one for periods between July 2017 and November 2020 and *LawInForce* represents the periods December 2020 to June 2021. Both variables represent the implementation process of the RNPA. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author’s table.

1.B Alternative Definition of Railroad Tracks

In Germany, the railroad network is not limited to freight train corridors. To ensure robustness, this check includes all main railroads combining passenger transport and cargo while excluding freight train corridors. The data used for this analysis is provided by UBA (2019e) for 2017 and includes railroads that register at least 30,000 trains annually. Figure 1.B.1 displays these tracks as orange lines, while the previously used network of freight train corridors is shown as black lines for reference. It is important to note that there are overlaps between both railroad systems. Neither transports solely goods or passengers, but the freight train corridors are the main tracks for national and international cargo transport by train.

The methodology remains unchanged to test the impact of the RNPA using this alternative set of railroads. A buffer of 500 m is constructed around the main tracks, which is then linked to the house listings. I expect the estimated coefficient will be smaller because the RNPA focuses on improvements in the cargo sector. The positive effect should be reduced when considering all main tracks because the mixture of trains and tracks should make the impact of the RNPA less recognizable and dilute the effect.

Figure 1.B.1: Alternative Railroads



Notes: The map shows the freight train corridors used previously in the analysis (black lines) and the main railroads with at least 30,000 trains per year in Germany (orange lines) as used in the robustness section.
Source: Author's graph. The track information is given by UBA (2019e) and European Commission (2021). State borders are given by Federal Agency for Cartography and Geodesy (2019).

Table 1.B.2 displays the outcomes when all main railroads replace the freight train corridors. The adoption effect increases to 1.0% compared to 0.5% in the baseline setting (see Table 1.3). The actual effect of the RNPA implementation is diminished to 2% as expected. The positive impact of the RNPA on reducing freight train noise is diluted when other railroad tracks, which are also used extensively for passenger transport, are included. This highlights the effectiveness of the RNPA specifically for freight trains.

Table 1.B.2: Additional Robustness Checks I: Alternative Railroads

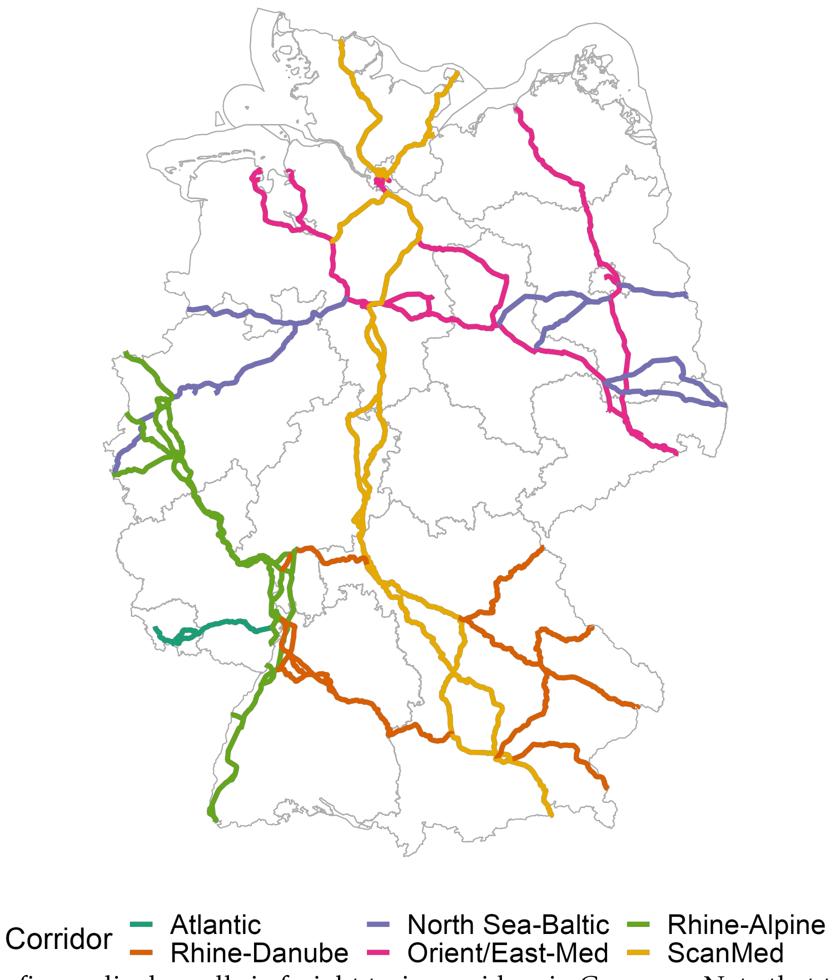
Dependent Variable:	log(house price)
	(1)
LawPassed × Buffer500	0.010***
	(0.001)
LawInForce × Buffer500	0.020***
	(0.003)
Full set of controls	✓
Fixed-effects	
Month FE	✓
Grid FE	✓
Fit statistics	
Observations	1,825,706
R^2	0.81842
Within R^2	0.50141

Notes: The table shows the results for replacing the freight train corridors by all main railroads. *Buffer500* indicates houses within 500 m of the tracks (treated). *LawPassed* is equal to one for periods between July 2017 and November 2020, and *LawInForce* represents the periods December 2020 to June 2021. Both variables represent the implementation process of the RNPA. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

1.C Leave-One-Out-Estimation

I also perform a leave-one-out-estimation where each of the corridors is excluded once. The network of freight train corridors consists of six single tracks highlighted in Figure 1.C.2. For the estimation, each corridor is dropped from the sample separately. The output can be found in Table 1.C.3.

Figure 1.C.2: Freight Train Corridors



Notes: The figure displays all six freight train corridors in Germany. Note that the corridors partially use the same tracks.
Source: Author's graph. The track information is given by European Commission (2021). State borders are given by Federal Agency for Cartography and Geodesy (2019).

Table 1.C.3 shows a consistent effect range across the corridors, with slightly more pronounced results after December 2020 (captured by *LawInForce*). The adoption period effect is insignificant when excluding the

North Rhine-Alpine corridor (column 4) and the Rhine-Danube corridor (column 5). After the RNPA has been fully adopted, the effect remains highly significant in all scenarios. The leave-one-out estimation results are similar to the baseline setting, which reinforces the previous findings.

Table 1.C.3: Additional Robustness Checks II: Leave-One-Out Estimation Corridors

Dependent Variable:	log(house price)					
Exclusion of	ScanMed	Orient East-Med	North Sea-Baltic	Rhine Alpine	Rhine Danube	Atlantic
	(1)	(2)	(3)	(4)	(5)	(6)
LawPassed × Buffer500	0.004**	0.010***	0.004**	0.001	0.003	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
LawInForce × Buffer500	0.028***	0.029***	0.023***	0.020***	0.023***	0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Full set of controls	✓	✓	✓	✓	✓	✓
Sample restricted	✓	✓	✓	✓	✓	✓
Fixed-effects						
Month FE	✓	✓	✓	✓	✓	✓
Grid FE	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	949,020	914,184	906,836	845,465	1,011,524	1,087,846
R^2	0.80733	0.82360	0.82820	0.82126	0.81864	0.82248
Within R^2	0.51429	0.52454	0.52081	0.48697	0.50766	0.50686

Notes: The table shows the outcome of repeated baseline regression with the exclusion of the ScanMed corridor in column (1), Orient/ East-Med corridor in column (2), North Sea-Baltic corridor in column (3), Rhine-Alpine corridor in column (4), Rhine-Danube corridor in column (5), and Atlantic corridor in column (6). *Buffer500* indicates houses within 500 m of the tracks (treated). *LawPassed* is equal to one for periods between July 2017 and November 2020, and *LawInForce* represents the periods December 2020 to June 2021. Both variables represent the implementation process of the RNPA. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

1.D Impact of Noise Barriers

For the final exercise, I include additional information regarding noise barriers in the model. The data, provided by FRA (2021), offers the geographical location of noise barriers along the main tracks. I use the information to calculate the straight-line distance between the housing unit and the nearest noise barrier.

Note that I do not use the information in the main specifications as the data does not contain when the noise barrier was installed. Therefore, it is possible that I may assume the presence of a noise barrier near a certain house being sold, but this assumption may be incorrect. Additionally, I have included regional fixed effects based on a one-square-kilometer grid, which should account for most of the impact of any omitted noise prevention measures in the main specifications. Based on this reasoning, I expect that the inclusion of the distance to noise barriers will not significantly alter the previous findings. The output is displayed in Table 1.D.4.

The analysis shows that including noise barriers as an additional covariate does not change the baseline results. The coefficients are identical to previous findings.

Table 1.D.4: Additional Robustness Checks III: Inclusion of Noise Barriers

Dependent Variable:	log(house price)
	(1)
LawPassed × Buffer500	0.005***
	(0.002)
LawInForce × Buffer500	0.025***
	(0.003)
Full set of controls	✓
Fixed-effects	
Month FE	✓
Grid FE	✓
Fit statistics	
Observations	1,142,975
R^2	0.82050
Within R^2	0.51012

Notes: The table displays the regression output when adding the distance to noise barriers to the model. *Buffer500* indicates houses within 500 m of the tracks (treated). *LawPassed* is equal to one for periods between July 2017 and November 2020, and *LawInForce* represents the periods December 2020 to June 2021. Both variables represent the implementation process of the RNPA. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

CHAPTER 2

Housing Prices, Airport Noise and an Unforeseeable Event of Silence

Chapter Abstract

To assess the causal impact of noise exposure on housing prices, we utilized a sudden and significant reduction in flight traffic that occurred due to the COVID-19 measures in Germany. Using a difference-in-difference approach to compare locations with varying levels of pre-pandemic noise exposure, we find a 2.3% increase in prices for apartments that experienced a reduction in noise. By disentangling the temporal dynamics, we find a peak effect in mid-2021, which has resulted in an increase of up to 6%. However, it is still unclear whether these effects will persist. While most evaluations suggest that the erection of a disamenity negatively affects prices, our research shows that lifting the burden enables neighborhoods to immediately catch up. This immediate catch-up contradicts the idea that housing prices are sticky with respect to (temporal) local factors. The temporal pattern indicates a significant increase in the effects during the pandemic, which suggests the presence of information asymmetries. This is because buyers may not be aware of the non-pandemic noise level during the pandemic.

JEL codes: O18, Q53

Keywords: COVID-19 pandemic, Aircraft noise, Housing prices, Hedonic function.

This chapter is co-authored with Philipp Breidenbach. A similar version has been published as Breidenbach, P. and Thiel, P. (2023). Housing Prices, Airport Noise and an Unforeseeable Event of Silence. *Ruhr Economic Papers No. 1020*. https://doi.org/10.4419/96973186. The chapter has also been invited for resubmission to the *Journal of Housing Economics*.

2.1 Introduction

Noise pollution is linked to significant costs that affect the physical, mental, and social well-being of local residents. Over the past decade, numerous studies have provided evidence of the substantial impact of airports and the associated noise pollution on health (e.g., Boes et al., 2013; Schlenker and Walker, 2016) and well-being (e.g., Lawton and Fujiwara, 2016). These negative outcomes are typically associated with a decrease in the value of living in such exposed areas. Literature suggests that environmental pollution has led to a decline in housing prices. Housing values are not only relevant concerning the housing market, but they also give important insights into people's reactions when exposed to environmental pollution. As housing prices are available via online platforms on a precise spatial and temporal information level, they form a prominent outcome in the causal analyses of environmental pollution in urban and regional economics.

Our study evaluates the effects of reduced aircraft noise during the COVID-19 (Coronavirus disease 2019) pandemic lockdown in Germany, which began in March 2020 and resulted in a significant decrease in travel and flights. While many studies on the effects of noise focus on the deterioration of the status quo (i.e., additional noise), our study examines an improvement in the current situation: specifically, a reduction in airport noise and its impact on housing prices.

Our approach has three key advantages compared to many other studies in the literature. Firstly, the COVID-19 pandemic's global lockdowns were unpredictable. As the most prominent non-pharmaceutical measures to slow down the spread of the virus, lockdowns with travel bans and closed borders were installed immediately after the outbreak. This led to a significant decrease in aviation activities at German airports. Therefore, we can objectively classify the reduction in noise as an exogenous event. As a result, our study is not affected by announcement effects or other influences of political lobbying that may raise concerns about estimated effects in other scenarios where noise pollution changes.

Secondly, our setup enables the analysis of events, reducing noise in areas of intense exposure. Studies that focus, for instance, on changes in routing are unable to derive estimated effects from strongly exposed areas, as those routes necessarily remain unchanged in the immediate proximity to the runway. Our setup reveals changes throughout the entire distribution of noise exposure. Due to the pandemic, aviation noise has been reduced in areas that were previously strongly and weakly affected. The spatial heterogeneity of the noise exposure can provide valuable insights into the varying levels of noise reduction.

Thirdly, the various stages of the pandemic enable us to measure a reduction in noise exposure with varying expectations for future noise levels, particularly in relation to the aviation market's future. Initially, during the first phase of the COVID-19 pandemic, it was expected that air traffic would quickly return to previous levels once the pandemic was over. However, as the pandemic progressed, it became increasingly clear that air traffic would be permanently restrained. This is especially relevant to the rise of virtual meetings, which may reduce the need for business travel in the long term, and the ongoing government efforts to limit CO_2 emissions. To achieve the ambitious emission reduction targets, reducing domestic flights (and overall flight activity) appears to be a viable strategy for meeting future emission goals. Currently, the future development of the German aviation market remains unclear. Although global air traffic is recovering strongly, inner-German flights are still significantly below pre-pandemic levels.

We build our analyses on a data set linking German apartment listings and contours of aviation noise surrounding German airports, which are provided by the Federal Environmental Agency (UBA, 2019a). The listings data, including characteristics and prices, are taken from the RWI-GEO-RED data set, which includes all listings from the German market leader in housing advertisements, ImmoScout24 (RWI, 2022a).[1]

We focus on apartments for sale.[2] By utilizing individual listings, we can take advantage of the precise geographical location information provided in RWI-GEO-RED, which enables us to directly link the housing data to the aviation-noise contour information surrounding the airports. These noise contours illustrate the aviation noise exposure of each location surrounding the airport (before the pandemic). By merging the data on noise and housing

[1]A detailed description can be found in Schaffner (2020).

[2]We also provide results for the data sets "houses for sale", "apartments for rent", and for the combination of apartments and houses for sale in the appendix (see Section 2.C).

listings, a detailed impression of the noise pollution affecting each individual listing is obtained.

Using a hedonic framework with a difference-in-difference approach, we can identify the causal effects of the treatment on the treated. The framework considers the detailed information on noise pollution and the time of the listing for each apartment, as well as the location in a noise-exposed area and the time before and after the onset of the pandemic. The treatment group consists of apartments located within the noise contour of an airport that are affected by severe aviation noise (above 55 decibels (dB) before the pandemic). The control group comprises only those apartments that are also located close to the airport but are not declared to be affected by noise.

To ensure that both groups are not affected substantially differently by other developments during the pandemic (e.g., local lockdown measures or shocks in specific branches), the control group is defined in close proximity. Furthermore, any contradicting effects of the decline of flights (and noise), such as job losses at the airport or aligned businesses, should affect both groups equally. Focusing on a geographically restricted sample can help to identify pure noise effects, as demonstrated by Breidenbach et al. (2021) using a similar setup. Our results suggest that noise reduction has a positive effect on housing prices, with a 2.3% increase observed in the baseline specification. The effect is stronger in neighborhoods with higher noise levels. While there are no significant effects in the first months of the COVID-19 outbreak (March 2020 marking the first lockdown in Germany), we observe an increase in apartment prices of about 4% during the summer of 2020. The same is true for spring 2021, when COVID-19 occurrences were relatively low and restrictions were generally lifted, we find the strongest effect of up to 6%. The effect may reflect residents' expectations that the aviation sector will not quickly recover to the pre-crisis level, even if the aviation sector is not actually affected by concrete lockdown measures anymore. Thus, the effect may indicate a shift in residents' perceptions that pollution will remain lower permanently compared to the pre-COVID-19 period. However, the effect decays in 2022, the time when the pandemic is increasingly considered to be over.

Our study contributes to the literature in two important ways. Firstly, we approach the relationship between housing prices and disamenities in a way that differs from most other studies. Rather than evaluating the negative impact of disamenities on apartment prices, we demonstrate a positive effect resulting from the alleviation of disamenities. However, academic research has not yet explored fully whether neighborhoods that were previously exposed to persistent disamenities can recover once the disamenity is removed. It is reasonable to assume that decades of exposure to aircraft noise may have additional socio-structural effects, such as the departure of better-off households from the affected neighborhoods to avoid the noise, while lower prices may have attracted worse-off households. Therefore, it is not clear whether the reduction of aircraft noise will result in a positive price effect that is equal in magnitude to the negative effects caused by the onset of disamenities.

Secondly, the temporal pattern provides additional insights into expectations, adoption speed, and adoption ability of the housing market, as well as potential information asymmetries. The significant reaction of housing prices can be interpreted in various ways. Purchase prices should reflect the long-term value of the property and not be strongly influenced by short-term improvements in noise levels. Assuming that a 6% price premium during peak periods is not justified by the actual reduction in noise over the period of about two years, it appears that prices have overreacted during the pandemic. Possible alternative explanations arise from information asymmetries. For instance, out-of-town buyers who have never experienced local noise exposure before the pandemic may pay higher prices due to a lack of knowledge about future noise exposure. This finding may support the need for mandatory disclosure of noise exposure during the housing transaction process. Another explanation arises from uncertain expectations regarding the aviation market's development during and after the pandemic. Although air travel has increased significantly in 2022 (but below pre-crisis levels), there are also projections that air travel will decline in the long term due to the rise of virtual meetings and more environmentally conscious flying.

The chapter is structured as follows: Section 2.2 summarizes related studies and provides motivational background information. Section 2.3 describes the applied empirical strategy and the used data sources. Section 2.4 lists the results for baseline setting, the heterogeneity analysis, and the robustness tests. Section 2.5 concludes.

2.2 Background

From a theoretical perspective, airports can have ambiguous effects on the local community. On the one hand, they are important employers in the region, both directly (e.g., airport personnel or pilots) and indirectly through numerous suppliers (e.g., logistics and construction companies that offer their services to or rely on nearby airports). Additionally, airports play a central role in medium to long-distance travel. On the other hand, they can be major sources of air and noise pollution, making them a burden for those living nearby.

The ambiguous effects of airports are also reflected in the existing empirical evidence. In a meta-analysis, Nelson (2004) finds a negative relationship between air traffic-related noise and housing prices. Jud and Winkler (2006) add to this finding by suggesting a negative effect on housing prices due to the announced expansion of the Greensboro airport in North Carolina. Contrary to the negative effects mentioned, Brueckner (2003) finds a positive impact of airports on employment, while Tomkins et al. (1998) and McMillen (2004) reported a positive effect on house prices due to proximity to airports. These studies highlight the potential opposing effects of having an airport in the neighborhood. Focusing on only one aspect does not account for the multiple dimensions involved when studying airport noise (see, e.g., Espey and Lopez (2000); Lipscomb (2003); Cohen and Coughlin (2008, 2009); Ahlfeldt and Maennig (2010)). Exploiting both effects, Cohen and Coughlin (2008, 2009), and Lipscomb (2003) suggest that the positive effects of employment or proximity cannot counter the negative noise effects.

Most studies focus on house prices rather than apartments when evaluating the impact of airport noise. However, Boes and Nüesch (2011) conduct a study on the airport in Zurich (Switzerland) that used a change in flight regulations to demonstrate that an increase in air traffic-related noise leads to a decline in apartment rents by 0.5% per dB increase in noise. Similarly, Baranzini and Ramirez (2005) find that the airport in Geneva (Switzerland) had a similar effect, with a 1% decrease in apartment rents per dB increase in noise. In the German context, Winke (2017) finds that the expansion of the Frankfurt a.M. airport resulted in a 1.7% decrease in apartment prices per dB. The results for rental apartments appear to be smaller than those for the sales market, which is reasonable given that different expectations lead to buying or renting a home. Renters are expected to live at one location for a shorter period, so they would benefit less from noise reductions. Buyers are expected to stay in the same place for years or even decades, and they may consider not only their own benefit but also the potential increase in future purchase prices when eventually reselling the apartment. Therefore, they tend to value improvements in environmental noise more. Ahlfeldt and Maennig (2015) supports this argument by evaluating the perceptions of homeowners and renters regarding the proposal to build the new Berlin-Brandenburg airport and close the old Berlin-Tegel airport.

Analyzing airport noise presents a unique challenge due to the nature of airports as large infrastructure projects with predetermined locations well in advance of completion. Even expansions and decommissions are publicly announced. This open knowledge introduces the challenge of announcement effects, as people and housing markets may react once opening plans are published. Avoiding anticipation effects when analyzing aircraft noise poses substantial challenges.

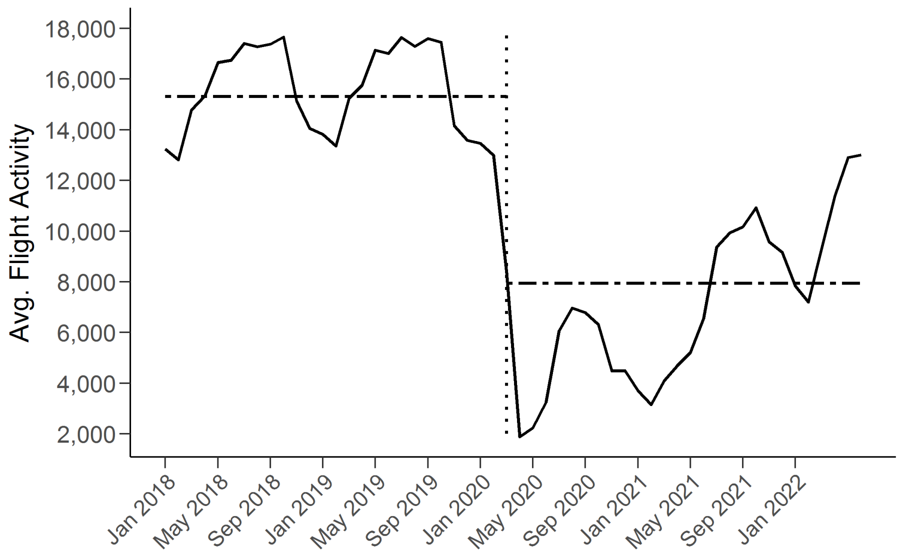
We have avoided most of the common problems in the literature. Our setup exploits the exogenous variation in airport-related noise due to COVID-19, allowing us to analyze the effect of airport noise on apartment prices without being concerned about announcement effects and the simultaneity of positive and negative effects. The COVID-19 crisis was not anticipated by airport operators or residents close by. In addition, the data set used provides precise geographical locations of apartments, enabling us to clearly define control and treatment groups that are equally affected by all airport effects except for noise.

Prior to the pandemic, air traffic was on the rise in many countries, including Germany. However, in March 2020, travel restrictions were implemented during the first lockdown to slow the spread of the virus. The reduction in airport noise due to the pandemic is well-documented in the decrease in flight activity at German airports between 2018 and 2022.[3] Figure 2.1

[3] Every take-off and landing is counted as a separate flight activity. Thus, one flight causes two activities.

displays the average flight activity for major airports.[4] The number of flights observed in the two years prior to the pandemic exhibited a clear seasonal pattern, with peaks of approximately 17,000 flights per month. However, during the first lockdown in April 2020, this number plummeted to less than 2,000 flights. In contrast to pre-pandemic years, the number of flights during vacation time in August 2020 only peaked at about 7,000. This is in comparison to about 11,000 flights during the same period in 2021, when travel bans were less restrictive, and about 13,000 flights in 2022, when there were no restrictions. Overall, the period averages (represented by dashed lines in Figure 2.1) indicate a difference of approximately 7,000 flights before and after the pandemic.[5]

Figure 2.1: Development of Average Flight Activity



Notes: The figure shows the average flight activity over time (January 2018 to June 2022) which includes starts and landings. The vertical line (dotted) represents the start of the pandemic in Germany, with the first lockdown in March 2020. The horizontal lines (dashed) represent the period average flight activity before (around 15,300 flights) and after the pandemic (around 7,900 flights).
Source: Authors' graph. The Federal Statistical Office (FOS, 2022) provides the raw data.

[4]Major airports are defined as airports that record at least 150,000 flight guest units annually. A flight guest unit represents either one passenger or 100 kilograms of cargo (FOS, 2022).

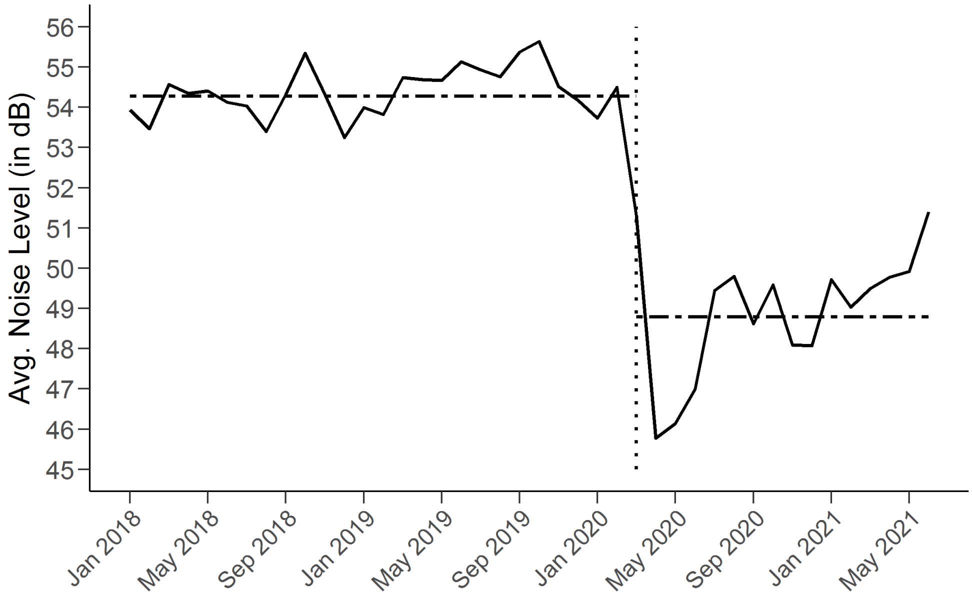
[5]The average flight activity across major airports before the pandemic was around 15,300 starts and landings, while the period average of the post-pandemic period is around 7,900 flights.

Currently, the aviation industry has yet to fully recover from the significant impact of the COVID-19 pandemic. Predicting the long-term growth of the aviation sector, including flight operations and noise pollution affecting nearby residents, is challenging.

The pandemic-induced reduction in flight activity has resulted in a corresponding decrease in air traffic-related noise. Figure 2.2 displays the average noise level over time at major airports.[6] The airports themselves provide the data. It is based on measuring stations close to airports and their runways. In pre-COVID times, the average noise level fluctuated between 54 dB and 55 dB, with an average of 54.3 dB (represented by the dashed line). Following the start of the pandemic, the noise level dropped to almost 45 dB in April 2020. Subsequently, the noise level slightly recovered, along with flight activity. The average noise level during this period was 48.8 dB (represented by the dashed line), which is still approximately 5 dB lower than the pre-treatment period. As a benchmark, a reduction in noise of 10 dB results in a perceived loudness decrease by half (Center for Disease Control and Prevention, 2019). Therefore, a reduction of 5 dB represents a significant difference. The drop due to the pandemic is, therefore, not just documented in summary statistics but is also highly detectable by ear. This amplifies our argument that the COVID-19 pandemic reduced aircraft-related noise, which impacts apartment prices in the proximity to airports.

[6] In contrast to our analysis, which covers the years until 2022, the figure illustrates the noise until mid-2021. Due to a changing composition in the noise stations, we cannot plot reliable data for a longer time period. We rely on the Day-Evening-Night level (LDEN) as a noise measure. LDEN summarizes the noise development over the entire day and adds an extra weight of 5 dB to evening times (7 pm to 11 pm) and 10 dB to night periods (11 pm to 7 am). This approach gives particular attention to noise-sensitive times.

Figure 2.2: Development of Average Noise Level



Notes: The figure displays the average noise level over time (January 2018 to June 2021) as measured by the Day-Evening-Night level (LDEN) in dB. The vertical line (dotted) represents the start of the pandemic in Germany, with the first lockdown in March 2020. The horizontal lines (dashed) represent the period average in aircraft-related noise before (around 54.3 dB) and after the pandemic (around 48.8 dB).
Source: Authors' graph. The airports themselves provide the raw data. It relies on measuring stations close to airports and their runways.

2.3 Empirical Setup and Data

2.3.1 Empirical Strategy

Our primary analysis focuses on apartments for sale. This is because apartments provide a sufficient number of observations exposed to airport noise, and their prices seem adequate to reflect the lift of disamenity in the long run. However, we also present results for two other housing types: houses for sale and rental apartments. Since the number of observations for houses in treated regions is quite low and the rents only partially cover the housing value, we focus on apartments for sale. Results for apartments for rent and houses for sale can be found in the appendix (see Section 2.C of the appendix).

We utilize a difference-in-difference approach to analyze a hedonic price function. Following Rosen's (1974) original framework, the hedonic model posits that the price of an apartment can be explained by its characteristics and surroundings. Our model takes the following form:

$$\begin{aligned} log(y_{itg}) = \beta X_{ig} + \gamma NoiseContour_i + \delta(Pandemic_t \times NoiseContour_i) \\ + Month_t + Grid_g + \epsilon_{itg}, \end{aligned} \tag{2.1}$$

The variable $log(y_{itg})$ represents the logarithm of the listing price of apartment i in year-month t and grid cell g. The control variables, including the characteristics of the apartment on level i, as well as the distances to large, medium, and small regional centers, the distance to the airports themselves, and the distances to other noise sources like railroads, industrial plants, and streets, are summarized in X.

The variable *NoiseContour* is a binary indicator that determines whether an apartment is located within the noise contour of a major airport. This means that the home is exposed to at least an air traffic-related noise level of 55 decibels (in pre-COVID times). The control group apartments are limited to a maximum distance of five kilometers from the border of the noise contour. We also try different definitions in the robustness section. It is important to note that the treatment assignment is done on the individual housing unit level. All apartments located within a one-kilometer buffer around the noise contour are excluded. This neutral zone eliminates all homes that may be affected by aircraft-related noise because they are located just at the border of the noise contour. This strategy provides a clear distinction between treated and non-treated apartments.[7] The variable *Pandemic* is a binary variable that equals one for periods after March 2020 and zero for periods prior to that. March 2020 is considered the start of the pandemic as the German federal government implemented the first lockdown that month to limit the spread of the virus. The interaction term *Pandemic* × *Noise Contour* combines the pandemic dummy and the previously described noise indicator. Our main coefficient of interest is represented by δ. The coefficient identifies the impact of noise on apartment prices for homes within the noise contour, compared to a counterfactual scenario without noise reduction. It represents the average treatment effect on the treated (ATT).

During the analysis, we divide the interaction term *Pandemic* × *Noise Contour* into pre- and post-pandemic time spans. This enables us to examine the time patterns during the pandemic and also to test for parallel trends between the control and treatment groups before the onset of the pandemic. Further, the variable *NoiseContour* is split based on the different levels of noise intensities, taking advantage of spatial heterogeneities.

To enhance the small-scale setting, we introduce grid and year-month fixed effects to control for invariant confounders. The regression is performed using robust standard errors. We also run the analysis with various levels of clustered standard errors in Section 2.D of the appendix. These different settings do not affect the overall conclusion.

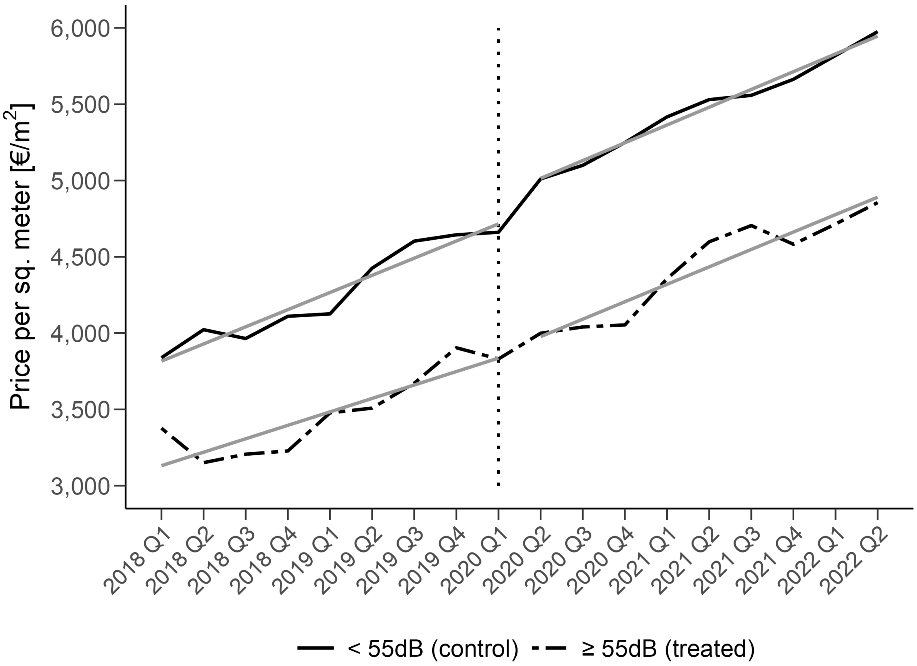
Since we are estimating a difference-in-difference model, it is crucial to consider the price development before the shock occurs for identification purposes. We plot the average price per square meter (in Euro) by quarters in Figure 2.3. From this, we can make three observations: Firstly, both the control and treatment groups exhibit an upward price trend. At the start of the observation period, prices for treated apartments ranged from 3,000 to 3,500 Euros/m^2, while the control group was just below 4,000 Euros/m^2. By the second quarter of 2022, prices had increased significantly to approximately 5,000 Euros/m^2 for the treated group and 6,000 Euros/m^2

[7] In one of the robustness checks, we relax this setting and include the neutral zone in the sample as part of the control group.

for the control group. This represents a substantial price increase over a relatively short period of time. The second observation is that the treatment region consistently exhibits lower price levels than the control group. The figure indicates that apartments located closer to airports, which are exposed to higher noise levels, sell for less on average. Additionally, the price curve of the treated apartments within the noise contour is more volatile than that of the control region. The difference in the number of observations between the treatment and control groups caused this issue. Despite this, both groups exhibit similar trends, which are tested econometrically in the results section.

Note that Figure 2.3 may suggest pre-COVID price effects in Q4 2019 and Q1 2020, but the figure only displays exploratory statistics without controlling for apartment characteristics. Our robustness checks indicate that there are no effects prior to the start of the pandemic when controlling for the discussed covariates, which eliminates any differences in groups prior to the shock. Further, trend lines suggest that there was an increase in price levels for the control group in the first quarter of 2020, but not for the treatment group. This contradicts our hypothesis that the treatment would result in an increase in apartment prices. It is important to note that this visual inspection alone cannot replace a comprehensive analysis. Local conditions should be taken into account when controlling for characteristics. Figure 2.E.1 in the appendix suggests that there may have been a change in the regional composition of the control group. Following the onset of the pandemic, there has been an increase in the share of apartments in the surrounding area of Frankfurt a.M. Airport within the control group. This change in the composition may also affect the presented mean price values. However, the empirical model outlined in this study includes grid fixed effects to control for these composition effects.

Figure 2.3: Apartment Price Development by Quarters



Notes: The figure shows prices per square meter by quarter for treated apartments (within the noise contour and exposed to at least 55 dB of air traffic noise) [dashed line] and control apartments (beyond noise contour and a noise level below 55 dB) [solid line]. The grey solid lines show the trends for the respective period and group. The vertical line represents the start of the pandemic (March 2020).
Source: Authors' graph.

2.3.2 Data

The pandemic and lockdown measures have substantially impacted the economy and society in various areas. Therefore, our identification strategy must present strong arguments demonstrating that the pandemic did not affect our treatment group differently from the control group through channels other than aviation noise. We focus on a geographically restricted area where the control and treatment groups are in close proximity to each other. This is to avoid potential differences, other than noise reduction, that may arise from a larger area.

Based on this spatially specific setup, we demonstrate that the control and treatment groups do not differ substantially in socio-economic characteristics. This supports the argument that the pandemic should not have affected these two groups differently, except for the described noise reduction for the treatment group. To ensure solid comparisons between the control and treatment groups in key socio-economic characteristics, we utilize the RWI-GEO-GRID data set (RWI, 2021). The RWI-GEO-GRID provides data on various characteristics, such as purchasing power and population, on a one-square-kilometer grid for all of Germany.[8] The comparisons presented are based on data from the year 2019, prior to the COVID-19 pandemic. Various variables were used, including demographic data such as household size and population density, as well as the proportion of the working-age population per grid (ages 18 to 65). Socio-economic indicators, such as annual household purchasing power (in Euros) and annual unemployment rate (as a percentage) per grid, were also taken into account. Table 2.1 shows the descriptive statistics calculated separately for the control and treated regions.

Table 2.1: Comparison of Treatment and Control Group in the Pre-Treatment Period

Variables	Control region		Treated region		t-test
	Mean	SD	Mean	SD	
Demographics					
Household density	967.65	1,726.90	683.48	1,205.41	6.26 (0.00)
Population density	1,815.16	3,075.94	1,346.98	2,370.48	5.45 (0.00)
Working population (%)	62.15	4.40	62.46	5.07	-1.88 (0.06)
Socioeconomic factors					
Puchasing power (EUR)	50,685.71	10,425.33	50,081.01	10,774.33	1.70 (0.09)
Unemployment rate (%)	4.66	3.37	4.85	3.52	-1.62 (0.10)

Notes: The table provides summary statistics (mean, standard deviation (SD), and t-test) comparing control and treated region in 2019, before the treatment occurred. The first group consists of grids beyond the noise contour and the latter is formed by grids within the contour.
Source: Authors' table. The data is provided by the RWI-GEO-GRID (RWI, 2021).

The demographic data indicates that there are differences in the number of people and households between the control and treated regions in their respective grid cells. We pay special attention to this point in our further analyses, as households might prefer the relocation to less populated areas as a reaction to the outbreak of COVID-19. We test for the impact of lower-density neighborhoods (in terms of people and households) in one of the robustness checks (see Section 2.4.3).

[8]The data was originally provided by microm GmbH. Breidenbach and Eilers (2018) offers a comprehensive description of the data.

The household purchasing power and unemployment rate are comparable between both groups, as shown in Table 2.1. The same applies to the working-age population. Examining the means and standard deviations indicates that COVID-19 has not affected the treatment and control groups differently, except for reducing noise.[9]

Overall, the summary statistics of the grid cells in the treated and control regions illustrate that the two groups share similar key economic characteristics. This strengthens the argument that we are comparing similar neighborhoods in our empirical setting. There is no evidence, except for the different population densities tackled in the robustness tests, that both groups are affected differently by the pandemic via channels other than noise exposure.

Our empirical strategy involves combining two primary data sources. We employ the RWI-GEO-RED data, which offers listings of apartments for sale made available on ImmoScout24.de (RWI, 2022a). Our observation period spans from January 2018 to June 2022. The RWI-GEO-RED data includes individual apartment prices on a monthly basis, along with various apartment characteristics such as size, number of rooms, and indicators for features like gardens or balconies. By utilizing precise geographical coordinates, we are able to accurately map each apartment to the noise contour of the nearest airport.[10]

During the data cleaning process, we exclude apartments with characteristic values below and above the 1^{st} and 99^{th} percentiles. The aim is to avoid unrealistic values resulting from fake listings and typing mistakes on ImmoScout24. Additionally, we exclude apartment listings from March 2020 (in the baseline setting) as this was the start of the pandemic. Since the apartment data is provided on a monthly basis, it is not possible to determine whether the March 2020 listings belong to the pre- or post-treatment period. For a detailed description of the dwelling data, see Schaffner (2020).

We link the housing data with our second data source, the noise contour maps of major airports from the Federal Environmental Agency (UBA, 2019a).

[9]There were no significant differences between the groups, as determined by a 5% significance level.

[10]We use the same data source for other housing types, such as houses for sale and apartment rentals, and apply the same empirical strategy. However, a causal interpretation cannot be made based on the results (refer to Section 2.C of the appendix).

These maps define areas around airports and their runways to indicate areas of particular noise exposure. The resulting noise levels typically range from 55 dB to above 75 dB. Therefore, the local community bears a significant burden. By definition, areas with airport noise levels below 55 dB are not considered to be noise-polluted. By merging both data sets, we can determine the noise level for each individual housing unit.

Figure 2.4 displays a noise contour map of Hamburg Airport as an example. The closer the distance to the airport and its runways, the higher the noise level. The left panel presents the noise contour rings, ranging from 55 dB to over 75 dB, as provided by the original source. The right panel consolidates the five rings into two due to fewer observations in the inner rings. This configuration is utilized in the subsequent heterogeneity analysis (refer to Section 2.4).

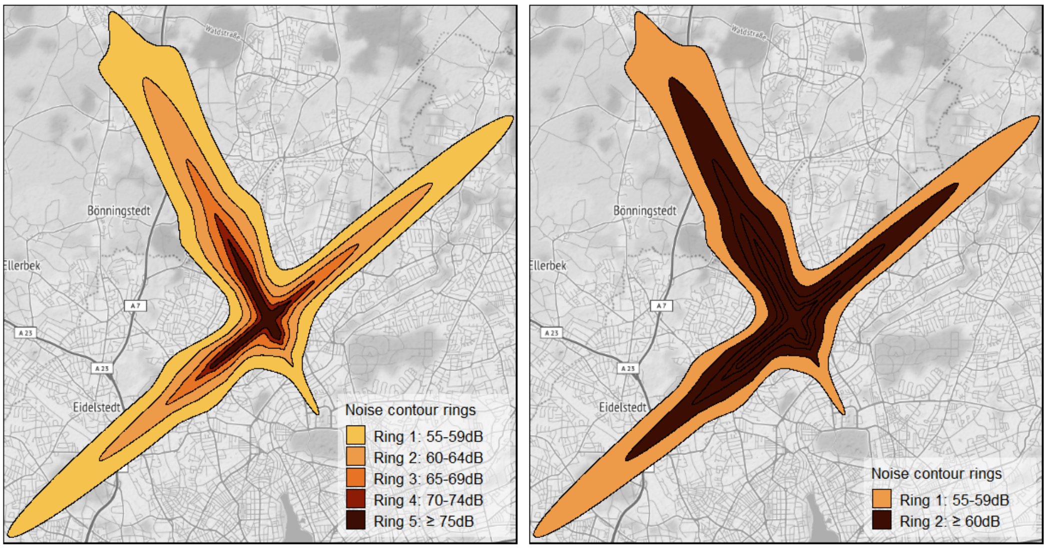
Note that the noise levels stated in these maps refer to pre-COVID times. The noise level dropped massively after the first lockdown as shown in Figure 2.2.

Our analysis is limited to the major airports in Germany, which are defined by the Federal Office of Statistics (FOS) as airports with at least 150,000 flight guest units per year.[11] In 2021, there were 23 primary airports in Germany, which accounted for 99% of the country's air transportation of passengers and goods (FOS, 2022). Only eleven maps are available since the FEA generates maps only for main airports that register a minimum of 50,000 air traffic movements.

Out of the eleven airports mentioned, two are located in Berlin. However, for two reasons, we exclude Berlin from our analysis. Firstly, Berlin had two airports for a long time – Berlin-Tegel and Berlin-Schoenefeld. The construction of the new airport, Berlin-Brandenburg, was planned to be completed in 2011, and Berlin-Tegel was supposed to shut down. However, due to construction delays, Berlin-Tegel remained open for business, leading to a ten-year period of uncertainty regarding its continuation. Berlin-Brandenburg was finally completed in 2020 and began operating in December of that year, resulting in the closure of Berlin-Tegel. Further, the new airport was merged with the existing Berlin-Schoenefeld, so the city only had one airport left. Due to these changes in the city's infrastructure and the uncertainty sur-

[11] One flight guest unit represents one passenger or 100 kilograms of cargo (FOS, 2022).

Figure 2.4: Noise Contour Map of the Hamburg Airport



(**a**) Original classification (**b**) Own classification

Notes: The figure shows the noise contour map of the Hamburg Airport as an example. The left panel shows the noise intervals as displayed in the original data. The right panel represents the zones as used in the analysis. The displayed noise intervals refer to pre-COVID times.
Source: Authors' graph. The contour information is given by Federal Environmental Agency (UBA, 2019a). The background map is constructed from the open-source Stamen Design.

rounding the opening of Berlin-Brandenburg and the closing of Berlin-Tegel, Berlin's airports are excluded.

The second reason to exclude Berlin is due to the city's decision to restrict rent development. In 2020, the Berlin Senate established a rent freeze (in German: Mietendeckel) to counteract the steady increase in the city's rent prices, aiming to stabilize rent levels for the next five years. However, the Federal Constitutional Court lifted this regulation in 2021. Similar to the airport situation, the apartment market involves some uncertainty. Although Berlin's regulations are focused on the rental market, it is possible that the impermanence has also affected the sales market. As we are studying the impact of noise reduction on apartment prices, this rent freeze clearly hinders the free development of the housing market. Therefore, our estimates may be compromised if Berlin is included in the sample.

Our analysis covers nine major airports, depicted in Figure 2.5. Although only nine of the original 23 major airports remain in the study, they account for a significant amount of air traffic, consolidating 77.6% of passenger transport and 95.6% of cargo among the main airports in 2019 (own calculation based on FOS, 2022).

Figure 2.5: Locations of Major Airports in Germany

Notes: The map shows the locations of the major airports included in the analysis.
Source: Authors' graph. The locations are given by UBA (2021). The spatial information of the states is given by the Federal Agency for Cartography and Geodesy (2019).

The data set is expanded by incorporating additional controls. Specifically, we include the Euclidean distance to the nearest regional centers as a covariate. The Federal Office for Building and Planning provides the definition of these centers (BBSR, 2020). We utilize the most recent data available from 2017. The BBSR identifies municipalities of regional importance through an accessibility model, resulting in the categorization of large, medium, and small centers.[12] Therefore, we aim to control for the interdependence between regions by including the distances to these regional centers. Additionally, commuting plays a central role for many households, which in turn impacts housing prices. By adding these variables to the analysis, we directly control for this relationship.

To control for its potential positive effect, we include the Euclidean distance to the airport building as another additional control variable. As outlined in Section 2.2, airports may have an ambiguous effect on housing prices. They can be seen as a disamenity due to noise and air pollution or as an economic hub, providing a working place either for people directly employed at the airport or for suppliers located close by. Additionally, they offer travel opportunities for medium to long-distance travel. Without this covariate, our estimates may be biased. UBA (2021) provides geographical information that includes a data set of all registered airports worldwide on openflights.org. In addition to the major airports shown in Figure 2.5, airports in agglomeration areas are also included in the list because they are eligible for the construction of noise maps by the FEA. This addition accounts for the possibility that the closest airport to a specific apartment may not be a major one but rather a city airport.[13]

We also include the Euclidean distance to other major noise sources, such as railroads, streets, and industrial plants. UBA (2018) provides data for major railroads, which includes all railroads registering at least 30,000 train movements annually. Similarly, we use the same data source to include the distance to major industrial plants in agglomeration areas (UBA, 2019b) and

[12]The goal is to guarantee equitable living conditions, even in remote areas (Friedrich et al., 2021). Regional centers offer a range of services to the local community, including shopping, leisure activities, transportation infrastructure, health care, and administrative services. The level of specialization and type of service provided depends on the center's size. Large and medium-sized regional centers offer different educational opportunities. While large centers provide specialized education with access to universities, specialized libraries, and museums, medium centers offer a broader education (Einig, 2015). Additionally, both large and medium centers are important for working and representing business centers (Friedrich et al., 2021) and can also be considered stabilizing factors, especially in remote areas (Milbert and Furkert, 2020).

[13]These airports are located in Essen/Mühlheim, Mannheim, Dortmund, Bremen, Mainz-Finthen, and Dresden. It is important to note that these airports are not included in the analysis due to registering less than 50,000 take-offs and landings per year and having only a few apartments in close proximity, resulting in a low number of observations. Therefore, they do not qualify for the regression analysis, and further analysis regarding the difference between main and regional airports is impossible.

distances to main streets with a traffic volume of at least 3 million cars per year (UBA, 2019c). By adding these additional noise sources, we can control for their negative impact on apartment prices. The estimates presented later reflect only the noise effect related to air traffic. It is important to note that all distances included in this text are calculated in kilometers.

Table 2.2 presents summary statistics for apartment characteristics and additional control variables. The table is divided into treated homes, which are within the noise contour and therefore exposed to aircraft noise, and control apartments that are not extensively affected by air traffic-related noise. The table also shows summary statistics before and after the first lockdown (March 2020) and provides unconditional difference-in-difference estimates.

Table 2.2 confirms the observation from Figure 2.3 that apartments exposed to aircraft-related noise sell for a lower price on average. Additionally, the table indicates that the treatment and control groups share similar key characteristics.

Table 2.2: Summary Statistics of the Housing Data

	Treated		Control		Uncond. DiD	
	Before pandemic	After pandemic	Before pandemic	After pandemic	Estimate	SE
	(1)	(2)	(3)	(4)	(5)	(6)
A. Housing characteristics						
Log(price)	12.47	12.70	12.58	12.85	−0.05***	0.01
Price (in Euro)	311,497.7	375,910.6	366,952.5	460,019.7	-28,654.4***	4,604.2
Living space	86.38	83.14	82.99	81.74	−1.99***	0.68
Number of rooms	2.94	2.89	2.85	2.84	−0.04*	0.02
Age	37.13	44.02	47.73	50.64	3.98***	0.49
Endowment	2.41	2.37	2.36	2.38	−0.05***	0.01
Bathrooms	1.17	1.18	1.15	1.16	−0.00	0.01
Floor	2.02	2.04	2.36	2.45	−0.07**	0.03
Heating type	10.2	9.95	9.99	9.67	0.07	0.09
Condition	5.15	5.35	5.42	5.30	0.32***	0.05
Balcony	0.81	0.77	0.77	0.76	−0.04***	0.00
Garden	0.19	0.21	0.18	0.18	0.01	0.00
Built-in kitchen	0.35	0.41	0.40	0.41	0.06***	0.01
B. Regional factors						
Dist. small regional center	10.53	10.19	9.87	9.71	−0.19	0.16
Dist. medium regional center	5.32	5.7	7.47	7.33	0.52***	0.06
Dist. large regional center	8.72	8.26	7.89	7.39	0.05	0.11
Dist. airport building	9.6	9.71	9.70	9.79	0.02	0.1
C. Additional noise sources						
Dist. railroads	1.25	1.18	1.13	1.12	−0.05**	0.02
Dist. industry	4.41	4.39	3.64	3.59	0.03	0.07
Dist. streets	0.45	0.47	0.98	0.87	0.14***	0.02
Observations	4,252	5,302	38,466	51,048	-	-

Notes: The table shows the mean of the used variables for treated apartments (i.e., within the airport noise contour) and control apartments (beyond noise contour) as well as before and after the start of the pandemic (March 2020). The columns (5) and (6) show the results for the unconditional difference-in-difference estimation.
Source: Authors' table.

2.4 Results

2.4.1 Main Results

Table 2.3 presents the baseline results.[14] Column (3) is our preferred specification, which includes time and regional fixed effects on a 1x1 kilometer grid level. The substantial reduction of noise pollution, which was unexpected, has a positive impact on apartments exposed to aviation noise. With the pandemic, which caused the reduction in noise, the listing price of these apartments increased by 2.3% compared to the control group apartments that were not exposed to noise (during normal times) but were also located near airports.[15]

Table 2.3 shows the significance of controlling for sound variables in the hedonic regression approach. Without controlling for individual dwelling conditions (column 1) and time-persistent differences in the local neighborhood on the grid level (column 2), the effect cannot be accurately estimated. Conducting an analysis without dwelling characteristics or with broader airport fix effects (instead of grid fix effects) results in no effect. The previously shown price trend graph (see Figure 2.3) visually confirms the finding, which is also supported by the unconditional difference-in-difference in Table 2.2.[16] In Section 2.B of the appendix, we also examine the impact of changing characteristics during the pandemic and still observe a positive effect of 2.2%. As the insertion of the local fixed effects has high relevance for the estimated coefficient, we test for the robustness of the results with respect to varying fixed effects, using 250x250 meter, 500x500 meter, 5x5

[14]Table 2.3 lists only the coefficients of interest. The full regression output with all covariates can be found in Section 2.A of the appendix.

[15]Note that we directly interpret the estimated coefficient as a percent change as the coefficients are relatively small. The precise interpretation following the formula $(e^{\delta} - 1) \times 100\%$ and δ being our coefficient of interest would result in an effect size of 2.31% (compared to 2.28% yield by the approximation).

[16]The changes of characteristics between treated and non-treated dwellings before and after the onset of the pandemic, as presented in Table 2.2, hint at the importance of the controls. The endowment and condition of treated dwellings worsened after the onset of the pandemic, while the control group did not experience the same decline. The same pattern is observed for the age of the building. Furthermore, the residences provided in the treated area post-pandemic are located farther from central areas, indicating that more remote locations are available in the treatment group. This emphasizes the significance of accurate local fixed effects, as provided by the 1x1 km grid fixed effects.

kilometer grids and zip-code fixed effects presented in Table 2.6.

Table 2.3: Baseline Results

Dependent Variable:	log(apartment price)		
	(1)	(2)	(3)
Pandemic × NoiseContour	−0.012	−0.005	0.023***
	(0.011)	(0.006)	(0.005)
Full set of controls		✓	✓
Fixed-effects			
Months	✓	✓	✓
Grids	✓		✓
Airports		✓	
Fit statistics			
Observations	97,501	97,499	97,499
R^2	0.52563	0.82334	0.91084
Within R^2	0.0000	0.77992	0.81203

Notes: The table shows the baseline results with *Pandemic* indicating periods after March 2020 (i.e., pre-treatment period) and *NoiseContour* being equal to one for apartments within the noise contour of major airports (i.e., treated). Column (1) shows the unconditional estimation without any controls. Column (2) shows the results with controls and fixed effects on the monthly and airport level. Column (3), our preferred specification, displays the output with controls and monthly and grid fixed effects. A full version of the table with all controls can be found in the appendix (see Section 2.A). Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

2.4.2 Heterogeneity Analysis

The baseline specification suggests a positive impact on apartment prices in the treated area after the pandemic-induced noise reductions. However, we are also interested in how this effect performs under different scenarios.

Heterogeneities in Noise Intensities

In the first heterogeneity test, we utilize the richness of our data by dividing the noise contour into two rings to examine the potential impact of noise intensity. If the baseline results continue to support the narrative that apartment prices respond positively to noise reductions, then it is expected that apartments with higher noise levels will exhibit a stronger response to decreasing noise levels.

The first ring summarizes noise levels ranging from 55 to 59 dB, while the second ring accounts for higher noise intensity, registering levels above 60 dB before the COVID-19 pandemic. Figure 2.4 (right panel) displays a graphical representation of these rings. This distinction enables us to identify the impact of noise reduction on apartments that were previously exposed to weak and strong noise levels.

Table 2.4 shows the main coefficient of interest for both levels of noise intensity.

Table 2.4: Heterogeneity Analysis: Noise Intensities

Dependent Variable:	log(apartment price)
	(1)
Pandemic × Ring 2_{High}	0.043***
	(0.011)
Pandemic × Ring 1_{Low}	0.018***
	(0.005)
Full set of controls	✓
Fixed-effects	
Months	✓
Grids	✓
Fit statistics	
Observations	99,066
R^2	0.91088
Within R^2	0.81184

Notes: The table shows the heterogeneity analysis assuming different noise intensities with Ring 1 indicating areas with a noise level of 55 to 59 dB (low noise before the pandemic) and Ring 2 identifying regions of noise levels above 60 dB (high noise). *Pandemic* indicates periods after March 2020. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

As expected, the impact is substantially larger for those apartments with higher noise exposure (4.3%) compared to the effect of 1.8% for the less affected apartments. These findings suggest that previously high noise levels are associated with stronger price reactions when experiencing noise reductions.

Heterogeneities in Time

Next, we will examine the temporal patterns of the effect throughout the pandemic. We analyze the various effects of the pandemic by dividing the post-pandemic period into three-month intervals and the pre-pandemic period into six-month intervals.[17] The reference period is March 2020. The period indicators are then interacted with the dummy variable that indicates proximity to airports (*NoiseContour*).

Figure 2.6 reports the results of these interaction terms graphically.

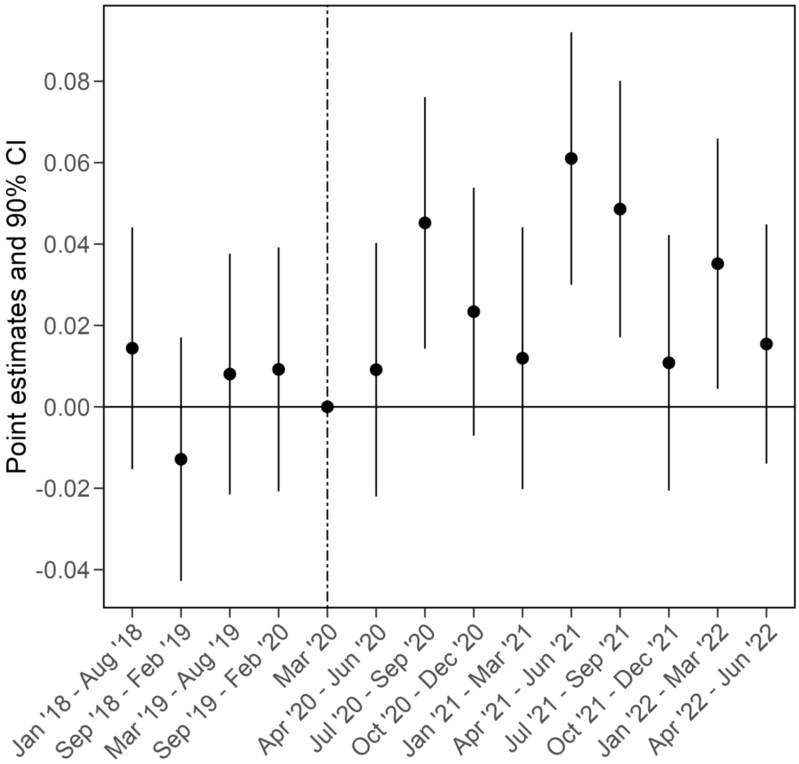
Figure 2.6 shows a temporal pattern throughout the pandemic. The initial period following the lockdown (April-June 2020) did not have any impact on apartment prices. This could be due to the widespread belief that COVID-19 measures were only temporary and would have a predictable end. The impact grew during the summer of 2020 when many national restrictions were lifted, but air travel had not yet returned to pre-pandemic levels. In the summer of 2021, the effect sizes were between 4.9% and 6.1%, which is the largest observed. This effect is observed despite the number of flights recovering to a lower level than before the pandemic. The perception of residents and people moving into such exposed neighborhoods that the aviation market will not fully recover may have caused this effect.

Finally, Figure 2.6 displays an increase of around 3.5% in the period of January to March 2022. These late positive effects suggest that the housing market is influenced by factors beyond the pandemic shock, despite reduced travel restrictions and increased flight activity. While the effects observed in 2020 and 2021 could be attributed to noise reductions, the findings in 2022 may be associated with changes in the aviation industry.

The perception of local residents towards the aviation sector during the pandemic remains unclear. Most of the pandemic measures have already been lifted in 2022. The number of aircraft movements at the airports under consideration has increased from approximately 50% of pre-pandemic levels during the pandemic to around 90% of pre-crisis levels by mid-2022 (refer to Figure 2.1). From this perspective (recovery of the aviation market to its

[17] The change from six months to three months is intended to study the temporal pattern in the post-treatment period, which may include seasonal variations. Although a six-month interval provides more power due to the higher number of observations per bin, it also absorbs the seasonal pattern due to the aggregation.

Figure 2.6: Heterogeneous Analysis: Temporal Dynamics



Notes: The figure states the heterogeneous effects over time by splitting the post-treatment period into intervals of three months and the pre-treatment period into six-month intervals. The reference period is March 2020 (dashed line). These intervals are then interacted with the treatment indicator (*NoiseContour*). Point estimates are indicated by dots. The vertical solid lines show the 90% confidence intervals (CI).
Source: Authors' graph.

original level), no effects of the pandemic on the housing market should be expected in the long term.

The price effects observed during the pandemic, especially the price peaks, may seem unexpected at first glance. These effects can be explained by either information asymmetries between buyers and sellers or an overreaction in price formation processes. Information asymmetries may have been present when buyers of real estate were unable to assess the pre-pandemic noise exposure of the offered properties. This may apply to buyers moving in from other regions. In this case, providing mandatory information about expected noise levels would benefit buyers by reducing asymmetries.

If buyers can accurately assess noise impacts, then they may have paid a price premium for temporarily mitigated noise impacts during the pandemic that may not be justified in the long term. As aircraft movements return to pre-pandemic levels, the observed price premiums may reflect amenities that only pay off during the pandemic.

Alternatively, it can be argued that noise from aviation may not return to pre-crisis levels. Evidence of this trend can be inferred from the stock prices of the aviation industry, which reflect the industry's long-term economic outlook (refer to Figure 2.F.2 in the appendix).[18] Another indication of this is provided by the fleet management of Lufthansa, the largest airline at German airports. They plan to reactivate only three of the 14 A380 aircraft that were originally operated.[19] These planes are the largest and, therefore, one of the noisiest aircraft types. Other airlines may also avoid starting operations with their oldest (and thus noisiest) aircraft types, even if they subsequently increase their operations. However, even if we assume lower future noise levels, the high price premium during the pandemic does not seem rational because prices would then have to remain at the same higher level in the long run. Although the data does not provide a clear indication of whether higher prices tend to persist, the peak effects are no longer reached.

2.4.3 Robustness Checks

To ensure the stability of our findings, we conduct several robustness tests. Firstly, we perform a placebo test by restricting our observation period to before March 2020 and moving the start of a placebo pandemic to March 2019. The results of the placebo test, presented in Table 2.5 (column 1), show no significant effect, thus strengthening the parallel trend assumption.

To test for unique developments on the municipality level, we add a

[18] The development of stock prices suggests persistent effects. To illustrate this, we have plotted the time trend for the German stock index, the DAX 40, which represents the entire economy, and air-traffic-related stocks. Both time series have been standardized to a value of 100 in the baseline period of January 2018. It is not surprising that aviation stocks, which outperformed the general economy before the crisis, experienced much stronger losses with the onset of the COVID-19 pandemic. Both stock bundles demonstrate a recovery process following the summer of 2020. The DAX even surpassed its pre-lockdown level in 2021. The aviation sector also experienced some recovery but stabilized at significantly lower levels. This may suggest rather permanent changes in the industry, at least in the medium term.

[19] Refer to https://www.aero.de/news-44365/Lufthansa-nennt-A380-Ziele.html [Accessed: February 2023].

municipality-specific time trend to the analysis. The effect magnitude decreases compared to the baseline finding but still points in a positive direction, indicating that apartments exposed to aircraft noise gained value after the event of silence (see Table 2.5 column 2).

The following two robustness checks concern regional population densities. As indicated in Table 2.1, the mean density of population and households are lower in the treated area.[20] Identification problems may arise due to the increasing value people place on lower-density areas following the onset of the COVID-19 pandemic. Therefore, our findings may be attributed to the rising popularity of sparsely populated areas rather than the reduction of noise caused by the pandemic. We test this hypothesis using the RWI-GEO-GRID data set (RWI, 2021) to identify less populated grids. We remove areas with less than 1,443 people and 716 households, which represents the 10% percentile, respectively. Columns (3) and (4) of Table 2.5 disperse the concerns that sparsely populated neighborhoods drive our findings as both tests show similar effects as before.

Our main specification excludes apartments that are located within one kilometer of the noise contour. They neither act as treatment nor as a control group. The intention was to establish a clear cut between the treatment and control group without including apartments in the control group that might be partially treated due to their closeness to the noise contour. On the contrary, one might argue that these apartments near the treated region are a perfect control group. It is important to ensure that all neighborhood characteristics are similar to those of the apartments affected by noise. To test the importance of apartments located within the previously neutral one-kilometer buffer zone, we reverse the previous setting and include the neutral zone. Column (1) of Table 2.6 shows that including the neutral zone reduces the previously found effect. The finding suggests the presence of spatial spillovers at the border of the noise contour, supporting the exclusion of the neutral zone to estimate a clear noise effect.

In all settings thus far, we have included regional fixed effects on a one-square-kilometer grid. We adjust the setting and add fixed effects for grid sizes of 250 m, 500 m, and 5 km. The smaller regional fixed effects are

[20] This result is not unexpected, as airports are often situated on the outskirts of urban areas where the population density is lower.

Table 2.5: Robustness Checks I: Placebo Test, Time Trend, and Regional Densities

Dependent Variable:	log(apartment price)			
	Placebo	Time trend	Population density	Household density
	(1)	(2)	(3)	(4)
Placebo pandemic × NoiseContour	0.001			
	(0.007)			
Pandemic × NoiseContour		0.018***	0.027***	0.027***
		(0.006)	(0.005)	(0.005)
Full set of controls	✓	✓	✓	✓
Time trend		✓		
Fixed-effects				
Months	✓	✓	✓	✓
Grids	✓	✓	✓	✓
Fit statistics				
Observations	40,668	97,499	87,705	87,703
R^2	0.91738	0.92092	0.90782	0.90725
Within R^2	0.80981	0.83328	0.81507	0.81453

Notes: The table displays several robustness tests, with column (1) showing the results for the placebo test and the pandemic starting in March 2019, column (2) adding a municipality time trend, column (3) and column (4) restricting the sample by dropping sparsely populated areas in terms of population and households, respectively. *Pandemic* indicates periods after March 2020, and $NoiseContour$ is equal to one for apartments within the noise contour of major airports. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

particularly strict in terms of unobserved characteristics that cannot be directly controlled for in the model. Table 2.6 demonstrates that our findings remain consistent despite the change in fixed effects. The data also indicates that incorporating zip-code fixed effects reduces the magnitude of the effect (see column 5). However, it is possible that these regional units are not precise enough to capture local conditions, which suggests the inclusion of smaller one-square-kilometer grids.

Finally, we also investigate the impact of modifying the control group definition. In the previous scenarios, we assigned all apartments beyond the noise contour but within 5 km to the control group. It can be argued that this setup includes control apartments that are quite far away from the airport and, therefore, differ in key characteristics. Additionally, apartments located in the heading of the runway may still be affected by noise since approaching

Table 2.6: Robustness Checks II: Neutral Zone and Regional Fixed Effects

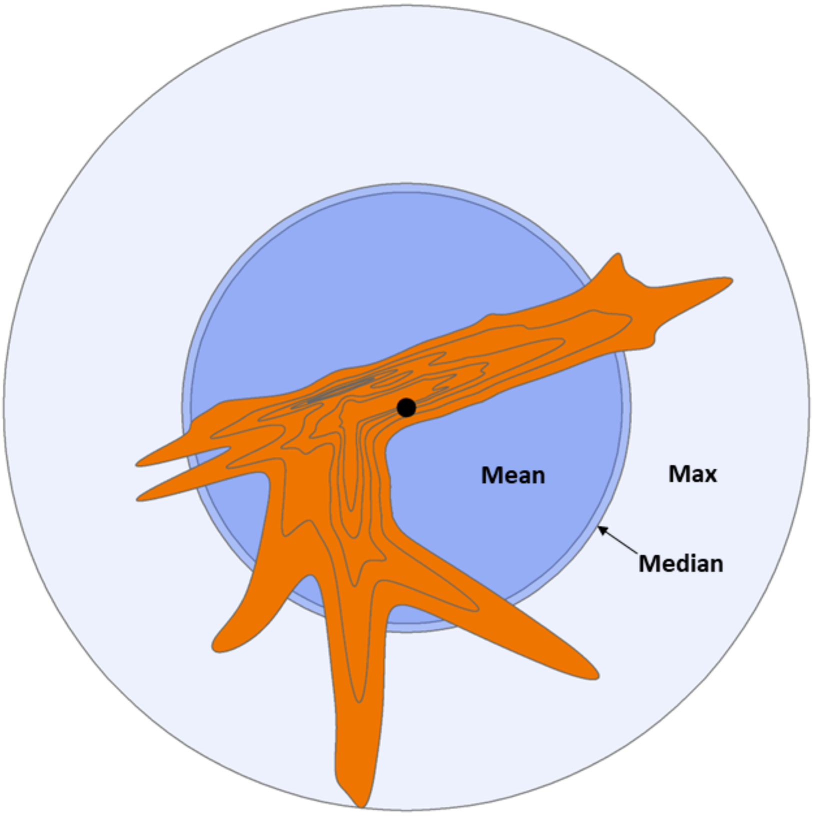
Dependent Variables:	log(apartment price)				
	Incl. NZ	250 m FE	500 m FE	5 km FE	Zip-code FE
	(1)	(2)	(3)	(4)	(5)
Pandemic × NoiseContour	0.018***	0.018***	0.022***	0.019***	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Full set of controls	✓	✓	✓	✓	✓
Fixed-effects					
Months	✓	✓	✓	✓	✓
1 km grids	✓				
250 m grids		✓			
500 m grids			✓		
5 km grids				✓	
Zipcode					✓
Fit statistics					
Observations	115,906	97,499	97,499	97,499	97,406
R^2	0.90887	0.94285	0.92572	0.87632	0.89511
Within R^2	0.81033	0.80878	0.81158	0.79972	0.81084

Notes: The table displays several robustness tests, with column (1) showing the results for including the neutral zone and column (2) to (4) varying the regional (grid) fixed effects from 250 m to 5 km. *Pandemic* indicates periods after March 2020, and $NoiseContour$ is equal to one for apartments within the noise contour of major airports. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

planes fly directly over them. They are exposed to noise that is only slightly below the observable exposure threshold of 55 dB.

For this robustness check, we use the airport building instead of the contour to calculate the distance between it and each point of the contour. We then calculate the mean, median, and maximum distances to draw circles around the airport building. All apartments within the circle but beyond the noise contour belong to the respective control group. The treatment group remains unchanged and contains homes within the contour. This forms a control group that is located closer to the airport. Airport-related shocks and (unobserved) socio-economic and geographical factors should be increasingly similar with a closer definition of both groups. Apartments located at the heading of the runway are excluded by definition. Figure 2.7 displays the definition of these distance rings for the Frankfurt a.M. airport. It is important to note that the distances used are specific to the airport and are based on individual contours. In Section 2.G of the appendix, we test for a static definition of the rings, meaning that they are the same for every airport, by defining zones up to 20 km.

Figure 2.7: Control Group Definition Based on Dynamic Distances: Frankfurt a.M. Airport



Notes: The figure represents a graphical representation of the control group definitions based on the distances between the airport building and the noise contour for the airport in Frankfurt a.M.
Source: Authors' graph.

Table 2.7 shows that shrinking the control group distances (mean and median specifications) leads to larger effects. Conversely, the magnitude of the effects is reduced when the distance is expanded to the maximum. However, our baseline finding remains unchanged even when the control group definition is altered. This test alleviates concerns that our main specification relies on apartments in the control group that are either far away or also exposed to noise, making them unsuitable for comparison with the treatment group.

Table 2.7: Robustness Checks III: Change of Control Group Definition - Dynamic Distances

Dependent Variable:	log(apartment price)		
	Mean distance	Median distance	Maximum distance
	(1)	(2)	(3)
Pandemic × NoiseContour	0.033***	0.035***	0.016***
	(0.005)	(0.005)	(0.005)
Full set of controls	✓	✓	✓
Fixed-effects			
Months	✓	✓	✓
Grids	✓	✓	✓
Fit statistics			
Observations	48,303	45,696	176,581
R^2	0.91318	0.91525	0.91138
Within R^2	0.82896	0.82677	0.80452

Notes: The table shows the regression output with varying distance measures for the control group. Column (1) refers to the control group based on the mean distance between the airport itself and the contour shape. Column (2) uses the median distance, and column (3) relies on the maximum distance. *Pandemic* indicates periods after March 2020. *NoiseContour* is equal to one for apartments within the noise contour of major airports. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

2.5 Conclusion

This chapter examines the relationship between housing prices and aircraft-related noise. Identifying the impact of airport noise is a challenging task due to the public knowledge of airport installations long before their completion. This raises the issue of announcement effects in any analysis of noise effects resulting from the opening of new airports or the expansion of existing ones.

To overcome this challenge, we utilize the COVID-19 lockdown in Germany during March 2020 as a source of variation in air traffic and aircraft-related noise. The aviation sector experienced a significant decline in flight activity due to travel bans and closed borders, resulting in a reduction in aviation noise. We apply a difference-in-difference approach to analyze this reduction. The study is based on a detailed data set that includes precise geographic coordinates of apartments and links them to noise contour maps of German airports. Additionally, we directly control for a comprehensive list of covariates to identify the impact of noise.

Our study demonstrates a positive impact on apartment prices when noise pollution is reduced unexpectedly. According to our baseline results, there is a 2.3% increase in prices after the pandemic began, indicating a recovery process for treated apartments once excessive noise is reduced. We conduct various robustness checks to confirm our findings, including changes in the sample, the introduction of different fixed effects, and modifications to the control group definition. All tests support our findings.

The heterogeneity analysis reveals an even larger effect on apartments that experienced higher noise levels before the onset of the pandemic. These apartments show a stronger reaction to the noise reduction compared to apartments that were less affected. Additionally, the effect displays distinct temporal patterns. In 2021, during the mid-stages of the pandemic, the effect reaches its peak at approximately 5% to 6%. In the first quarter of 2022, we find significant effects, but they become insignificant in the second quarter. It is uncertain whether the aviation market in Germany will return to its previous level of activity or if noise-polluted areas will continue to experience reduced noise pollution. Therefore, we cannot determine from a theoretical perspective whether a price effect is warranted by long-term changes in noise exposure.

Our study adds to the existing literature by demonstrating that the removal of a disamenity, such as high noise exposure, results in rapid reactions in the housing market without any price stickiness. Although the effect's peak does not persist over time, we observe that the housing market tends to overreact to the elimination of disamenity by exceeding prices, given the regeneration of air traffic over time. Information asymmetries may explain the strong effects on the temporal improvement of noise reduction. Buyers who have never experienced noise exposure may not be aware of future exposure when purchasing an apartment in the treated area. Mandatory disclosures can help prevent such information asymmetries.

In a broader context, these results can be applied to evaluate the effectiveness of local environmental policies for urban planning. Most studies analyzing noise pollution use setups with increasing noise levels, but we demonstrate the effects of reducing such noise pollution. As soon as noise levels are expected to decrease, locations previously affected by noise pollution quickly recover.

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Appendix

2.A Full Baseline Results Table

Table 2.A.1: Full Baseline Results

Dependent Variable:	log(apartment price)		
	(1)	(2)	(3)
A. Housing characteristics			
Age		-0.001^{***}	-0.002^{***}
		(0.000)	(0.000)
Age^2		0.000^{***}	0.000^{***}
		(0.000)	(0.000)
Living space		0.026^{***}	0.024^{***}
		(0.000)	(0.000)
Living space^2		0.000^{***}	0.000^{***}
		(0.000)	(0.000)
Floor		0.003^{***}	0.004^{***}
		(0.001)	(0.000)
Floor (unknown)		-0.048^{***}	-0.033^{***}
		(0.002)	(0.002)
Balcony		0.005^{**}	0.016^{***}
		(0.002)	(0.002)
Condition: First occupancy after reconstruction		-0.066^{***}	-0.072^{***}
		(0.005)	(0.005)
Condition: Like new		-0.083^{***}	-0.117^{***}
		(0.004)	(0.003)
Condition: Reconstructed		-0.180^{***}	-0.181^{***}
		(0.005)	(0.004)

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Table 2.A.1 – *Continued from previous page*

Dependent Variable:	log(apartment price)		
	(1)	(2)	(3)
Condition: Modernized		−0.224***	−0.209***
		(0.004)	(0.003)
Condition: Completely renovated		−0.202***	−0.193***
		(0.005)	(0.004)
Condition: Well-kept		−0.249***	−0.238***
		(0.003)	(0.003)
Condition: Needs renovation		−0.337***	−0.324***
		(0.006)	(0.005)
Condition: By arrangement		−0.239***	−0.261***
		(0.019)	(0.016)
Condition: Dilapidated		−1.921***	−1.770***
		(0.009)	(0.048)
Condition (unknown)		0.023***	0.018***
		(0.003)	(0.002)
Number of rooms		−0.040***	−0.003**
		(0.002)	(0.001)
Built-in kitchen		0.031***	0.014***
		(0.002)	(0.002)
Garden		0.025***	0.023***
		(0.002)	(0.002)
Heating: Electric heating		−0.095***	−0.071***
		(0.016)	(0.012)
Heating: Self-contained central heating		0.053***	−0.014**
		(0.008)	(0.006)
Heating: District heating		0.017**	−0.018***
		(0.008)	(0.006)
Heating: Floor heating		0.105***	0.057***
		(0.007)	(0.006)
Heating: Gas heating		0.039***	−0.007
		(0.008)	(0.006)
Heating: Wood pellet heating		−0.070***	−0.024**
		(0.016)	(0.012)
Heating: Night storage heating		−0.084***	−0.096***
		(0.019)	(0.014)
Heating: Heating by stove		−0.055***	−0.097***
		(0.015)	(0.014)
Heating: Oil heating		−0.049***	−0.045***

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Table 2.A.1 – *Continued from previous page*

Dependent Variable:	log(apartment price)		
	(1)	(2)	(3)
		(0.010)	(0.008)
Heating: Solar heating		0.149***	0.118***
		(0.045)	(0.027)
Heating: Thermal heat pump		0.071***	0.057***
		(0.009)	(0.007)
Heating: Central heating		0.010	−0.017***
		(0.007)	(0.006)
Heating (unknown)		−0.018***	−0.021***
		(0.003)	(0.002)
Endowment: Normal		0.077***	0.069***
		(0.008)	(0.006)
Endowment: Sophisticated		0.202***	0.160***
		(0.008)	(0.006)
Endowment: Deluxe		0.325***	0.233***
		(0.009)	(0.007)
Endowment (unknown)		0.052***	0.037***
		(0.003)	(0.002)
Number bathrooms		0.015***	−0.010***
		(0.003)	(0.002)
Number bathrooms (unknown)		−0.064***	−0.055***
		(0.003)	(0.002)
B. Regional factors			
Distance to large regional center		−0.009***	−0.005
		(0.000)	(0.003)
Distance to medium regional center		0.040***	0.038***
		(0.000)	(0.003)
Distance to small regional center		0.015***	0.029***
		(0.000)	(0.003)
Distance to airport building		−0.008***	−0.014***
		(0.000)	(0.003)
C. Additional noise sources			
Distance to industrial plants		−0.013***	0.031***
		(0.000)	(0.003)
Distance to railroads		0.000	0.015***
		(0.001)	(0.004)
Distance to streets		−0.034***	0.006
		(0.001)	(0.005)

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Table 2.A.1 – *Continued from previous page*

Dependent Variable:	log(apartment price)		
	(1)	(2)	(3)
D. Effects of interest			
NoiseContour	0.137	−0.120***	−0.029
	(0.115)	(0.005)	(0.033)
Pandemic × NoiseContour	−0.012	−0.005	0.023***
	(0.011)	(0.006)	(0.005)
Fixed-effects			
Months	✓	✓	✓
Grids	✓		✓
Airports		✓	
Fit statistics			
Observations	97,501	97,499	97,499
R^2	0.52563	0.82334	0.91084
Within R^2	0.00000	0.77992	0.81203

Notes: The table shows the full output table for the baseline specification with *Pandemic* indicating periods after March 2020 (i.e., pre-treatment period) and *NoiseContour* being equal to one for apartments within the noise contour of major airports (i.e., treated). Column (1) shows the unconditional estimation without any controls. Column (2) shows the results with controls and fixed effects on the monthly and airport level. Column (3), our preferred specification, displays the output with controls and monthly and grid fixed effects. The table corresponds to the abbreviated version in the main text (see Table 2.3). Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

2.B Baseline Analysis with Time-Interacted Characteristics

A potential concern is that the changing housing characteristics during the pandemic may have caused differences between the treatment and control groups, leading to the estimated effect. To address this concern, we estimate a model in which each control variable is interacted with time (year-month). This captures any heterogeneity in characteristics resulting from developments within the groups over time.

The estimated effect is highly similar to the baseline effect, with a difference of only 0.1% (2.2% compared to 2.3%). Therefore, our setup is resilient to changes in housing characteristics.

Table 2.B.2: Baseline Results with Time-Interacted Characteristics

Dependent Variable:	log(apartment price)
	(1)
Pandemic × NoiseContour	0.022***
	(0.005)
Full set of controls	✓
Controls interacted with time	✓
Fixed-effects	
Months	✓
Grids	✓
Fit statistics	
Observations	97,499
R^2	0.91693
Within R^2	0.82487

Notes: The table shows the baseline results where each control variable is interacted with time (year-month) to simultaneously to control for changes in housing characteristics. *Pandemic* indicates periods after March 2020. *NoiseContour* is equal to one for objects within the noise contour of major airports. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

2.C Analysis of House Prices and Apartment Rents

We also examine the effect of pandemic-induced noise reduction on real estate prices for private houses and apartment rents. We also combine sales data for houses and apartments in one specification. The RWI offers information on apartments for rent (RWI, 2022b) and houses for sale (RWI, 2022c). The data has the same structure as our main data set for apartments for sale.

Note that home characteristics may vary slightly between houses and apartments for sale. For instance, the estimation of house prices includes the house's plot area and the number of floors, which is not applicable to apartments. Therefore, only matching characteristics are included when both data sets are combined (column (2) Table 2.C.3). The estimation of apartment rents includes the same housing characteristics as the main specification, but the dependent variable changes to the rent per square meter. All other controls remain identical to the previous settings. The methodology also remains unchanged.

The results suggest a smaller impact of the noise reductions due to the pandemic on house sales than for apartments (1.7% compared to 2.3% for apartments). The combination of both data sets reveals an almost identical effect to the main setting. The estimation for apartment rents shows an effect of 2.1%.

All regressions show a consistent response to the reduction in noise levels across the housing markets. However, we do not include either house sales or apartment rents in our main specification because the pre-trend assumption for some periods does not hold. This violation compromises the validity of the identified effects with respect to houses and rents and weakens the interpretation.

Table 2.C.3: Estimation Results for Other Housing Types

Dependent Variable:	log(house price)	log(price)	log(rent per m^2)
Data:	HS	HS & AS	AR
	(1)	(2)	(3)
Pandemic × NoiseContour	0.017***	0.022***	0.021***
	(0.006)	(0.004)	(0.002)
Full set of controls	✓	✓	✓
Fixed-effects			
Months	✓	✓	✓
Grids	✓	✓	✓
Fit statistics			
Observations	55,171	152,670	328,695
R^2	0.81985	0.87229	0.68606
Within R^2	0.57074	0.79080	0.29939

Notes: The table shows the baseline setting for houses for sale (HS) in column (1), the combination of house and apartment sales (HS & AS) in column (2) and apartment for rents (AR) in column (3). *Pandemic* indicates periods after March 2020. *NoiseContour* is equal to one for objects within the noise contour of major airports. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

2.D Analysis with Clustered Standard Errors

Our primary analysis employs robust standard errors. We assign the housing units on an individual level to the noise contour to define treated apartments, making clustering unnecessary. Additionally, the COVID-19 shock affects the entire country, and therefore, noise reduction occurs simultaneously. However, some may argue that cluster application is necessary for this type of analysis.

Table 2.D.4 offers insights about various clustering levels (grids, municipalities, and districts). The significance level drops to 5% compared to the baseline setting. Note that these regional levels do not match the one of the analysis or treatment assignment.

Table 2.D.4: Additional Robustness Checks I: Clustering

Dependent Variable:	log(apartment price)		
	Grid	Municipality	District
	(1)	(2)	(3)
Pandemic × NoiseContour	0.023**	0.023**	0.023**
	(0.011)	(0.009)	(0.011)
Full set of controls	✓	✓	✓
Fixed-effects			
Months	✓	✓	✓
Grids	✓	✓	✓
Fit statistics			
Observations	97,499	97,499	97,499
R^2	0.91084	0.91084	0.91084
Within R^2	0.81203	0.81203	0.81203

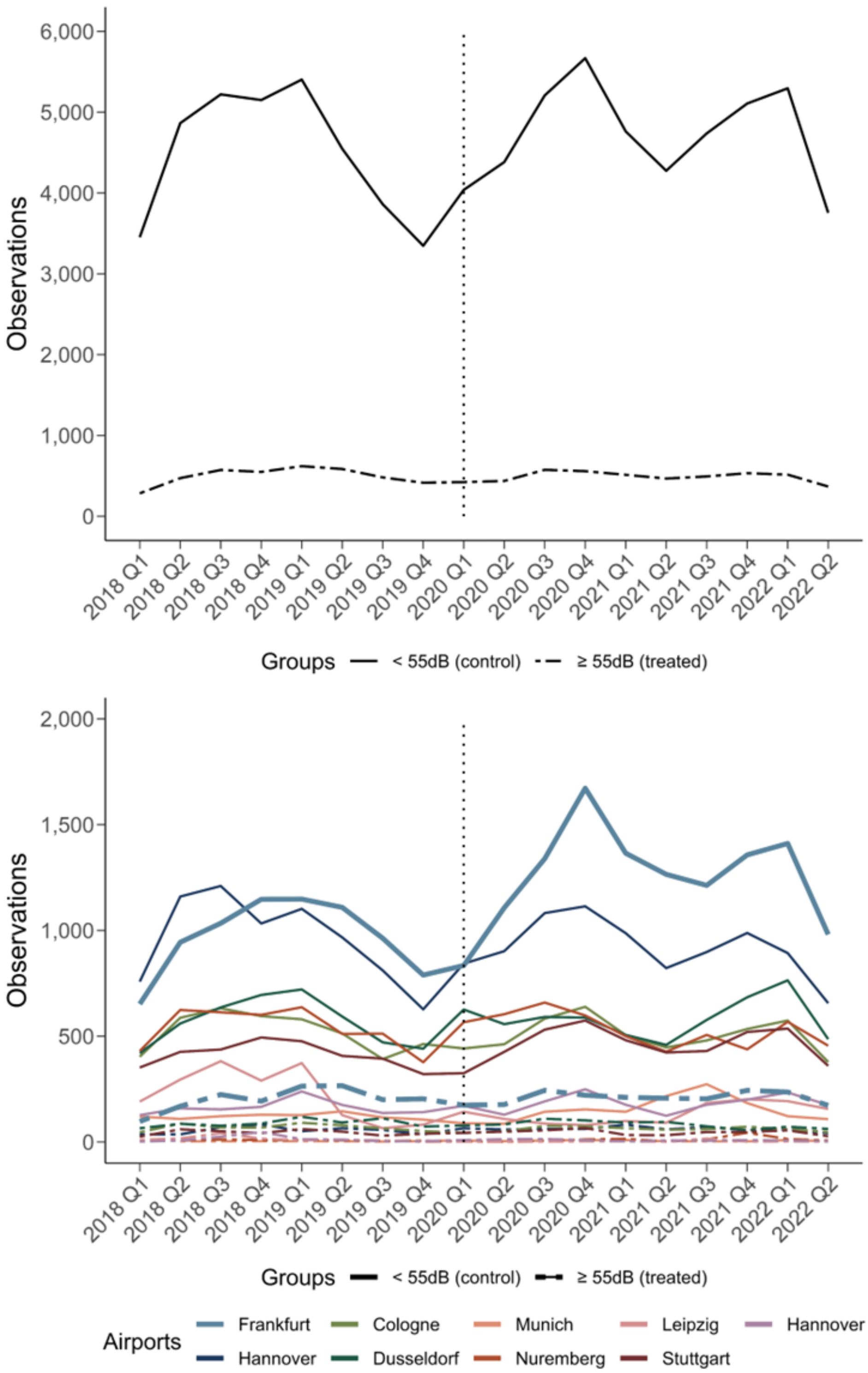
Notes: The table shows the regression output for various levels of clusters (grids, municipalities, and districts). *Pandemic* indicates periods after March 2020 and *NoiseContour* being equal to one for apartments within the noise contour of major airports. Cluster standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

2.E Number of Observations

Figure 2.E.1 displays the number of observations over time (top panel) and for each airport (bottom panel) for the treatment group (dashed lines) and control group (solid lines). Regardless of the airport, the control group includes more apartments than the treatment group. The figure also indicates that the number of observations increased at the beginning of the pandemic, particularly for Frankfurt a.M. Airport (represented by bold lines).

The figure also shows why conducting a sub-analysis for individual airports is not feasible due to the small number of observations for each airport. Although analyzing the differences between passenger and cargo airports may be interesting, it is not possible with the available data.

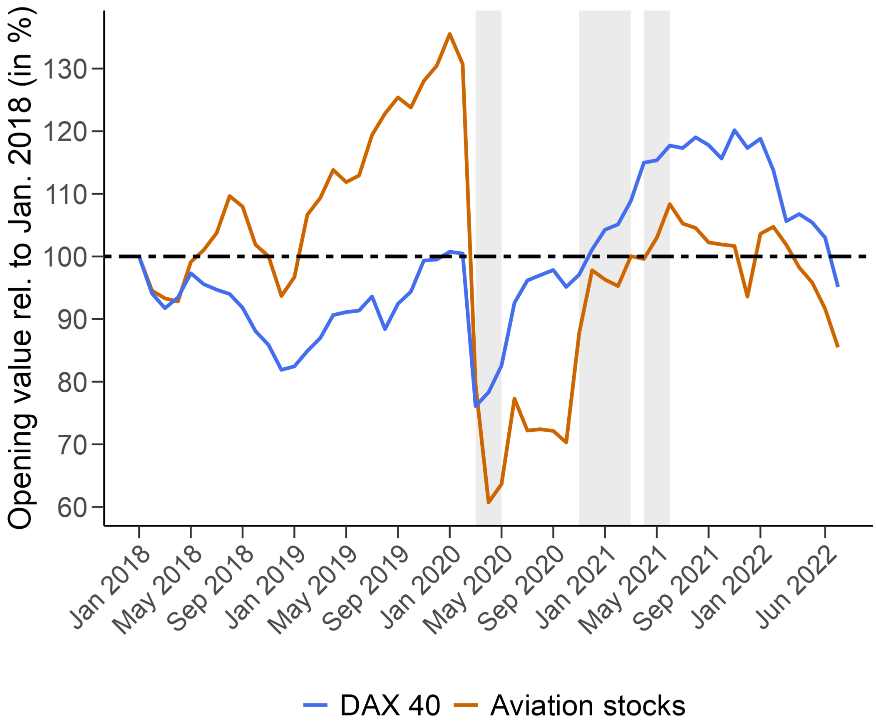
Figure 2.E.1: Number of Observations by Quarter and by Airport



Notes: The figures show the number of observations by treatment (dashed) and control group (solid) over time (top panel) and by airports (bottom panel). Frankfurt a.M. airport, as the largest airport, is indicated in bold in the bottom panel. The vertical line (dotted) indicates the start of the pandemic in March 2020.
Source: Authors' graph.

2.F Stock Market Development in the Aviation Sector

Figure 2.F.2: Development of DAX 40 and Aviation Stocks



Notes: The figure shows the development of DAX 40 (blue) and aviation stocks (orange) over time (January 2018 to June 2022). We plot the average opening value relative to the value in January 2018 (= 100%) in percent. The vertical lines (grey) represent the first and second lockdown as well as the so-called *Bundesnotbremse*, which provided regions with tools to implement lockdown-like measures once the incidence exceeded the threshold of 100 (7-day average).
Source: Authors' graph. Ariva.de provides the raw stock market data.

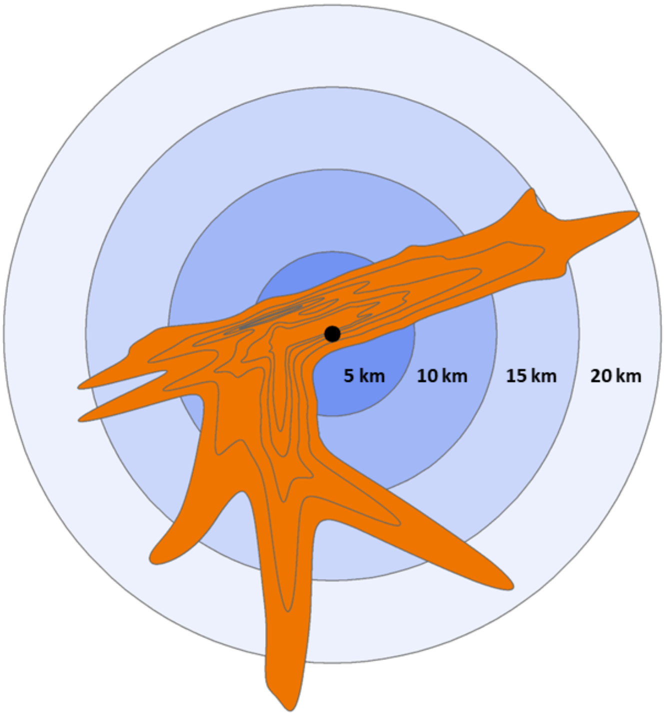
2.G Change of Control Group Definition - Static Distances

In the previous settings, we defined the control group as being outside the noise contour of the respective airport, limited to 5 km in the baseline, or restricted by (dynamic) distances based on the airport and the contour in the robustness section. However, for this additional test, we opt for a more static approach and defined the control group based on fixed distances from the airport. Specifically, we draw circles with radii ranging from 5 km to 20 km around the airport and include all apartments within these areas that are beyond the noise contour in the control group.

Note that these static distances are the same for all airports. Previous measures based on contour shape vary by airport. Therefore, these settings consider the unique circumstances of each airport.

Figure 2.G.3 displays the circle definition of the Frankfurt a.M. Airport. Note that the neutral zone (1 km around the noise contour) is also excluded in this setting as well.

Figure 2.G.3: Control Group Definition Based on Static Distances: Frankfurt a.M. Airport



Notes: The figure shows the graphical representation of the control group definitions based on the static distances around the airport in Frankfurt a.M.
Source: Authors' graph.

Table 2.G.5 suggests that our results are robust to different definitions of the control group. The restriction to 5 km and 10 km show the same effects as the main specification. The other two distances have smaller effects. The test allays concerns that the previously selected control group may not be suitable for identifying the positive effects of noise reductions on housing values.

Table 2.G.5: Additional Robustness Checks II: Change of Control Group Distance - Static Distances

Dependent Variable:	log(apartment price)			
	Restr. 5km	Restr. 10km	Restr. 15km	Restr. 20km
	(1)	(2)	(3)	(4)
Pandemic × NoiseContour	0.023***	0.023***	0.018***	0.016***
	(0.006)	(0.005)	(0.005)	(0.004)
Full set of control	✓	✓	✓	✓
Fixed-effects				
Months	✓	✓	✓	✓
Grids	✓	✓	✓	✓
Fit statistics				
Observations	19,826	84,222	157,524	227,473
R^2	0.90578	0.90839	0.91249	0.91407
Within R^2	0.82759	0.82523	0.80914	0.79509

Notes: The table shows the regression output with varying static distance measures for the control group. Column (1) restricts the control group to 5 km, column (2) to 10 km, column (3) to 15 km, and column (4) to 20 km around the airport building. *Pandemic* indicates periods after March 2020 and *NoiseContour* being equal to one for apartments within the noise contour of major airports. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

CHAPTER 3

Heterogeneous Pass-Through Over Time and Space: The Case of Germany's Fuel Tax Discount

Chapter Abstract

Exploiting exogenous variation in retail fuel prices from a temporary fuel tax discount in Germany, which was effective from June to August 2022, we estimate how the pass-through of this discount varies over time and space. To this end, we draw on daily gasoline prices of virtually all gas stations in Germany and neighboring France, with France serving as a control. Based on a difference-in-differences approach, we find average pass-through rates on the order of 96% for diesel and 86% for petrol, but with substantially lower rates in high-income regions or in regions with a low degree of competition. Our results also suggest pronounced heterogeneity over time. The magnitude of the pass-through rate dissipates sharply over the three months in which the discount was in effect, a pattern consistent with retailer responses to short-term changes in consumer attention. Overall, our results suggest that average pass-through estimates may obscure a high degree of spatial and temporal heterogeneity that bears upon the assessment of competition and distributional effects.

JEL codes: L13, L81, D43
Keywords: Competition, Demand elasticity, Fuel Tax Discount, Gasoline market.

This chapter is co-authored with Manuel Frondel and Colin Vance.

3.1 Introduction

The high visibility of gas prices makes motorists keenly aware of when cost shocks reach the pump, often compelling policymakers to respond by reducing fuel taxes. This was the case in Germany after the Russian attack on Ukraine in March 2022, when fuel prices rose sharply to reach record levels of over 2 Euros per liter.

In response, the German government passed legislation to reduce fuel taxes – the so-called Fuel Tax Discount (FTD) – for a period of three months, from June 1^{st} to August 31^{st}, 2022. Accounting for the reduction in the value-added tax, the discount amounted to 35.16 Cents for petrol and 16.71 Cents for diesel. The discount aimed to provide financial relief to motorists, assuming that retail filling stations would fully pass on the tax reduction to consumers. Whether such full pass-through, in fact, transpires is a fundamental question of public economics, one whose relevance extends to concerns about market power, price dispersion, competition policy, and distributional implications. Yet, although theoretical analysis shows that competition is a key determinant of pass-through (Weyl and Fabinger, 2013), empirical evidence on this issue is scant.

Drawing on station-level panel data from Germany and France, with France serving as a control site, we take up this question and, first, pursue a difference-in-differences approach and, second, undertake an event study to investigate the pass-through of the tax discount and its heterogeneity over time and space for both fuel types, petrol and diesel. Germany offers a particularly interesting setting for addressing this issue because of a longstanding public perception that quoting a widely read newspaper, "competition on the fuel market does not function particularly well" (Süddeutsche Zeitung, 2022).

This perception led Germany's Federal Cartel Office to undertake a study on price setting in 2011, which concluded that a handful of companies exercise market-dominating influence as oligopolists, leading to higher gas prices than would otherwise prevail under perfect competition (Bundeskartellamt, 2011). A subsequent report by the International Energy Agency contradicts this assessment, concluding that "Germany has a largely deregulated and competitive oil market" with "a large number of independents in the refining and retail sectors" (IEA, 2012, p. 8). The tax discount, which constituted an unanticipated and exogenous change to the fuel price, affords the opportunity to scrutinize these opposing perspectives by analyzing how retailers pass on the discount to consumers.

Economic theory predicts that under perfect competition, the pass-through rate will vary between zero and one depending on the elasticity of supply and demand. Given the infinitely elastic supply and downward-sloping demand, the rate will equal one, implying that the full cost (or discount) from a tax change is passed to consumers. Recent analyses of the German Fuel Tax Discount (FTD) suggest that the pass-through rate is indeed close to one (Fuest et al., 2022; Schmerer and Hansen, 2023), corroborating earlier studies that find near full shifting in the US market (Chouinard and Perloff, 2004, 2007; Marion and Muehlegger, 2011; Li et al., 2014). Other scholars have pointed to the possibility of differential pass-through rates according to differences in local market structure. Theoretical analysis indicates that competition is a particularly important determinant of pass-through, one that depends fundamentally on the convexity of demand. Presuming that demand is not too convex, the pass-through rate increases with increases in competition, while it decreases when demand is highly convex (Weyl and Fabinger, 2013). The upshot is that imperfect competition renders a range of pass-through rates possible, including values that fall below zero (Alexandrov, 2014; Gayle and Lin, 2021) or that exceed one (Barzel, 1976; Kenkel, 2005; Pless and van Benthem, 2019).

A challenge facing empirical investigations is that the convexity of demand is typically unknown. Nevertheless, several studies have found that, consistent with linear (or not too convex) demand, pass-through increases with competition. In the retail gas sector, Doyle and Samphantharak's (2008) analysis of a tax moratorium in the Midwest reveals pass-through rates ranging from 70% to 100%, with less than full shifting occurring where market concentration is lower. This result aligns with Alm et al. (2009) and Byrne (2019), who find lower pass-through rates in rural areas of the US, where less competition is expected to prevail. More recently, Genakos and Pagliero (2022) examine a tax change on petroleum products among isolated markets in the Greek islands, allowing them to pinpoint how pass-through varies with changes in the number of competitors. They obtain estimates ranging from 40% in markets with a single retailer to 100% in markets with four or more competitors.

Building on the above studies, this study's overarching contribution is to consider both the supply- and demand-side channels through which tax changes are passed through to retail gas prices, recognizing that each channel is relevant to the question of competition. Three features distinguish our analysis: First, it allows for differential pass-through rates according to regional income levels, a thus far largely unexplored source of heterogeneity. To the extent that income moderates the demand elasticity for fuel (Kayser, 2000; Wadud et al., 2010), which in turn moderates competition through an industry conduct parameter (Weyl and Fabinger, 2013), it is a potentially important determinant of pass-through, with implications for both incidence and distributional effects among consumer groups. In one of the few papers to analyze this issue, Harju et al. (2022) find lower pass-through of a carbon tax among gas stations in high-income areas of Finland, from which they conclude that ignoring pass-through heterogeneity leads to an underestimation of the degree of regressivity.

Second, our competition analysis uses a novel measure based on the spatial concentration of retail fuel outlets and registered vehicles, thereby combining both the demand and supply sides. In contrast, many existing studies measure competition by focusing exclusively on the supply side, using the count of stations in a region or, as in Alm et al. (2009) and Doyle and Samphantharak (2008), by geographical designations that are correlated with station density, such as urban versus rural. Our measure instead normalizes the count of stations by the count of regionally registered cars. The denominator of the resulting ratio thereby allows for the possibility that two stations with the same number of competitors face different levels of demand and, hence, a different degree of competition.

Third, beyond reporting a time-averaged pass-through rate, we employ an event study specification that allows us to track how the rate evolves over the entire time period that the discount is in effect. This allows us to gauge the speed of adjustment to the discount, which we find to be almost immediate, as well as its persistence.

Not least, following Alberini et al. (2022), we complete our analysis by an auxiliary estimation exercise of a fuel consumption model to estimate fuel price elasticities for both petrol and diesel fuel using household data from the German Mobility Panel. By revealing the extent of demand convexity, these estimates allow us to sign the expected effect of differences in competition on the pass-through rate. The estimates also serve to anticipate differences in pass-through between petrol and diesel fuel (see Section 3.A of the appendix).

Among our key findings is an overall pass-through rate of 86% for petrol and, consistent with the lower demand elasticity for diesel estimated from the household model, a higher pass-through rate of 96% for diesel. We find that these rates increase with increases in the level of regional competition, which is likewise consistent with the quasi-linear demand identified from the model of fuel consumption, while they decrease with increases in income. Perhaps most strikingly, although the discount is passed on in full by the first day, its magnitude begins to dissipate rapidly roughly 30 days after its introduction, reaching a rate of less than 10% by the end of the period. We interpret this pattern through the lens of consumer search theory, positing that it reflects retailer responses to changes in consumer attention. The overall picture is thus one of pronounced heterogeneity over space and time, with a sizeable share of the population facing substantially less than full pass-through for much of the period.

The chapter is organized as follows. Section 3.2 discusses how the pass-through of tax changes is determined theoretically. It also describes the role of competition and the impact of demand. Section 3.3 describes our data sources and the empirical strategy we use to estimate pass-through rates. Section 3.4 shows the results. Section 3.5 concludes.

3.2 Theoretical Background

The pass-through rate of a tax is defined as the ratio of the change in price p due to a subsidy s (see, e.g., Weyl and Fabinger (2013)):

$$\rho := -\frac{dp}{ds}. \tag{3.1}$$

Under perfect competition, pass-through depends exclusively on the elasticities of demand and supply, ϵ_D and ϵ_S, respectively:[1]

$$\rho = \frac{1}{1 + \frac{\epsilon_D}{\epsilon_S}}, \tag{3.2}$$

where $\epsilon_D := -p/q \cdot dD(p)/dp$, $\epsilon_S := p/q \cdot dS(p)/dp$, and $D(p)$ and $S(p)$ denote demand and supply, respectively. Complete pass-through of the subsidy occurs when demand is perfectly inelastic, whereas zero pass-through occurs when demand is perfectly elastic. In other words, the more inelastic side of the market benefits from the subsidy.

To accommodate the possibility of imperfect competition, Weyl and Fabinger (2013) derive the following formula for the pass-through rate ρ that, in addition to the demand and supply elasticities, includes the inverse elasticities $1/\epsilon_{ms}$ and $1/\epsilon_\theta$, as well as the competition indicator θ:

$$\rho = \frac{1}{1 + \frac{\theta}{\epsilon_\theta} + \frac{\epsilon_D - \theta}{\epsilon_S} + \frac{\theta}{\epsilon_{ms}}}, \tag{3.3}$$

where, first, $1/\epsilon_\theta := q/\theta \cdot d\theta/dq$, and, second, $1/\epsilon_{ms} := dms/dq \cdot q/ms$ is the inverse elasticity of the marginal consumer surplus, $ms := -qp' = -q \cdot dp/dq$. ϵ_{ms} crucially determines the curvature of the logarithm of demand (Weyl

[1] To derive formula (3.2), starting with the equilibrium condition $D(p) = S(p+s)$ and differentiating this condition with respect to the subsidy s, we get:

$$D' \cdot dp/ds = S' \cdot (dp/ds + 1),$$

where $D' := dD(p)/dp$ and $S' := dS(p+s)/dp$ and hence,

$$\rho = -dp/ds = \frac{S'}{S' - D'} = \frac{\epsilon_S}{\epsilon_S + \epsilon_D}.$$

and Fabinger, 2013).[2] Third, parameter θ, called conduct parameter and defined as

$$\theta := \frac{p - mc}{p}\epsilon_D, \tag{3.4}$$

with mc designating marginal costs, is an indicator of competition: When θ equals zero, formula (3.3) collapses to formula (3.2) for perfect competition, whereas $\theta = 1$ indicates the polar case of pure monopoly.[3]

Empiricists typically make simplifying assumptions, one of which is that the competition parameter θ is invariant to changes in q, as under Cournot competition, implying that $1/\epsilon_\theta = 0$. In a similar vein, we assume that θ is invariant to tax changes, that is, that the intensity of competition remains unaltered, an assumption that seems reasonable given that we do not expect entry or exit of stations due to the short-term and quite surprising introduction of the tax discount. Another assumption that is typically invoked is constant marginal costs, which implies that ϵ_S is infinite. This assumption likewise seems reasonable over the short-run interval of the tax discount of three months. With these two assumptions, the terms $\frac{\theta}{\epsilon_\theta}$ and $\frac{\epsilon_D - \theta}{\epsilon_S}$ vanish from formula (3.3), resulting in:

$$\rho = \frac{1}{1 + \frac{\theta}{\epsilon_{ms}}}. \tag{3.5}$$

A third commonly invoked, but more difficult to justify assumption

[2] ϵ_{ms} is associated with the curvature of the logarithm of demand, because $(\log D)' = \frac{d \log D}{dp} = \frac{D'}{D} = \frac{1}{qp'} = -\frac{1}{ms}$, where $D = q$ and $D' = dD/dp = 1/(dp/dq) = 1/p'$ due to the derivative of the inverse function $D = (p(q))^{-1}$. The curvature of the logarithm of demand, given by the second derivative, then reads:

$$(\log D)'' = \frac{d}{dp}(-\frac{1}{ms}) = \frac{1}{ms^2}(\frac{d}{dq}ms) \cdot \frac{dq}{dp} = \frac{ms'}{ms^2} \cdot 1/p' = -\frac{1}{\epsilon_{ms}} \cdot \frac{1}{ms}(-\frac{1}{p'q}) = -\frac{1}{\epsilon_{ms}} \cdot \frac{1}{ms^2}.$$

Hence, the curvature crucially depends on ϵ_{ms}: $1/\epsilon_{ms} < 0$ always implies log-convex demand, log-concave demand always has $1/\epsilon_{ms} > 0$.

[3] Note that the definition of the parameter θ is due to the normalization of Lerner's rule, which states that the extent of the markup $p - mc$ depends on the elasticity of demand: $L := \frac{p-mc}{p} = 1/\epsilon_D$. While oligopolists and monopolists charge $p > mc$, so that the Lerner index is $L > 0$, a perfectly competitive firm charges $p = mc$, and, hence, $L = 0$, indicating that such a firm has no market power. By multiplying the Lerner index L with the demand elasticity ϵ_D, the resulting parameter θ is normalized: $0 \leq \theta \leq 1$, like the Lerner index, which ranges from 0 to 1, as well as.

is that demand is linear, implying that $\epsilon_{ms} = 1$.[4] When met, this linear-demand assumption implies that the pass-through rate ρ equals $1/(1+\theta)$. ρ increases with the parameter θ, that is, with competition. Violations of the linear-demand assumption, however, open the door to alternative outcomes: When demand is sufficiently convex, a case demonstrated by Pless and van Benthem (2019), increases in competition reduce pass-through and also allow the rate to exceed one. Consequently, the estimation of demand curvature that complements our analysis of pass-through allows us to relax the third assumption, providing a foundation for triangulating the observed empirical results with their theoretical underpinnings.

[4]Assume a linear demand function of the form $p(q) = a \cdot q + b$ with $a < 0$, then $p'(q) = a$ and marginal consumer surplus becomes $ms = -p' \cdot q = -a \cdot q$, so that $ms' := dms/dq = -a$. Hence, $\epsilon_{ms} := ms/(q \cdot ms') = -a \cdot q/(-a \cdot q) = 1$.

3.3 Data and Empirical Strategy

3.3.1 Data

The first of the two major data sources used in this analysis is drawn from an online portal referred to as the Market Transparency Unit for Fuels (MTU), established under legislation requiring that retail fuel stations in Germany continually post prices for diesel and petrol when prices are changed. The MTU additionally records sundry station characteristics, such as the station's geographical coordinates, brand name, and opening hours. We retrieved this data from a repository that hosts all station-level data since the initiation of the MTU in 2013.[5] In what follows, we present the estimation results for two fuel variants: diesel and E10, a petrol derivative that contains 10% ethanol.[6] It is considered more environmentally friendly than the petrol variant E5, as E10 has a higher percentage of ethanol than E5. In addition, E10 is usually cheaper than E5. We have also estimated the effect of the Fuel Tax Discount using E5 as a petrol derivative, with the results not differing much between these two types of petrol.

Our estimation strategy relies on neighboring France as a control group, which likewise maintains an online portal, Le Prix des Carburants, from which we retrieved prices for E10 and diesel, as well as the station coordinates. Altogether, the final data set contains information on 15,188 gas stations in Germany and 9,154 gas stations in France and, hence, effectively covers the entire market in each country, leaving us with about 2.2 million and 640,000 observations on German and French prices, respectively.[7]

The similar economic conditions and the long common border between Germany and France speak for using the latter as a control site, but also raise the concern that the Stable Unit Treatment Value Assumption (SUTVA)

[5]See the website Tankerkoenig, where the data are offered for scientific purposes: https://dev.azure.com/tankerkoenig/_git/tankerkoenig-data.

[6]In 2022, about 48.5 million cars were registered in Germany, about 31 million (63.9%) petrol cars and 14.8 million (30.5%) diesel cars (see Federal Ministry for Digital and Transport, 2022).

[7]The lower number of observations for France is not only explained by the lower number of stations but also by the lower tendency to adjust prices.

could be violated.[8] Specifically, SUTVA rules out the existence of general equilibrium effects and treatment externalities, implying that the treatment solely exerts a direct effect on the unit being treated. The fact that French service station operators do not benefit from the tax reductions adopted in Germany partially assuages this concern, but they may nevertheless lower prices to attract German customers. We consequently plot the daily prices of French stations near the German border (see Figure 3.C.1 in the appendix), where such an incentive would presumably be strongest. We find that the price evolution of these stations does not differ from the French national level, arguing against a spatial spillover of the FTD. Furthermore, by including station-fixed effects, we control for any time-invariant differences that may exist between German and French stations, and by including day-fixed effects, we account for any shocks (e.g., fluctuations in the global oil market) that affect both countries.

We restrict our observation period to April 2022 to August 2022. This has two reasons: Firstly, France introduced its own policy to reduce fuel prices on April 1^{st} 2022. Extending the analysis horizon to months before April would mean we would include a shock in our control group, biasing our findings. Starting in April keeps the development of the control group constant in terms of policy interventions. For our empirical strategy and to identify the causal effect of the FTD, the parallel trends assumption must hold. We check for that in various analyses (e.g., visually in Figure 3.1 or more systematically in Section 3.F of the appendix) and find that our findings are robust against violations of the parallel assumption.

Secondly, we stop at the end of August 2022 because the FTD was limited to that period, and there were no plans for its continuation. Therefore, our treatment ended. Further, France updated its policy in September 2022. Figure 3.D.2 in the appendix shows the development of prices until November 2022. The prices in Germany and France diverge strongly after August, the end of the FTD. Any analysis beyond this point would not reflect pass-through related to the FTD, which ended in August, but other developments.

[8] France exports and imports the most products to and from Germany. On the other hand, France ranks third and fifth in Germany's export and import shares. France (Germany) has a population of 67.9 million (83.3 million) in 2022, and 17.4% (16%) of the population is between 15 and 29 years old. The GDP per capita in 2021 was 32,530 Euros in France and 35,480 Euros in Germany (see Eurostat, 2023; Worldbank, 2023).

3.3.2 Empirical Strategy

To capture the effect of the German Fuel Tax Discount, we pursue the following difference-in-difference approach:

$$y_{it} = \beta(FTD_t \times GER_i) + \gamma_i + \tau_t + \epsilon_{it} \tag{3.6}$$

We compare prices (y_{it}) before and after the introduction of the German fuel discount with prices in France for station i on day t.[9] FTD_t is the dummy indicating the fuel discount; it is set equal to one for periods after June 1^{st} 2022. GER_i is a dummy indicating stations in Germany, i.e., the treated region. The interaction between the two terms gives the average treatment effect of the treated, comparing prices at German stations with French prices before and after the introduction of the discount to the counterfactual without the discount. We also add station-fixed effects (γ_i) and time-fixed effects (τ_t) at the daily level. The standard errors are clustered at the station level.

Given the main coefficient of interest (β) and the relationship established in Equation (3.1), we can determine the pass-through rate in our setting as:

$$\hat{\rho} = -\frac{dp}{ds} = -\frac{\hat{\beta}}{FTD_{Petrol\,=\,35.16\text{ Cents or }Diesel\,=\,16.71\text{ Cents}}} \tag{3.7}$$

To capture the evolution of pass-through over the full period of the discount, we estimate also a subsequent model using an event study specification:

$$y_{it} = \sum_{t=1}^{T} \beta(Day_t \times GER_i) + \gamma_i + \tau_t + \epsilon_{it} \tag{3.8}$$

For the evolutionary effect, we interact the dummy for German stations (GER_i) with the variable Day_t, which indicates the specific day t. The interaction represents the daily effect with respect to May 31^{st}, the last day before the introduction of the FTD.

The key identification assumption underpinning the models is the parallel trends assumption: in the absence of treatment, the difference in fuel prices between the treatment and the control group is assumed to be constant

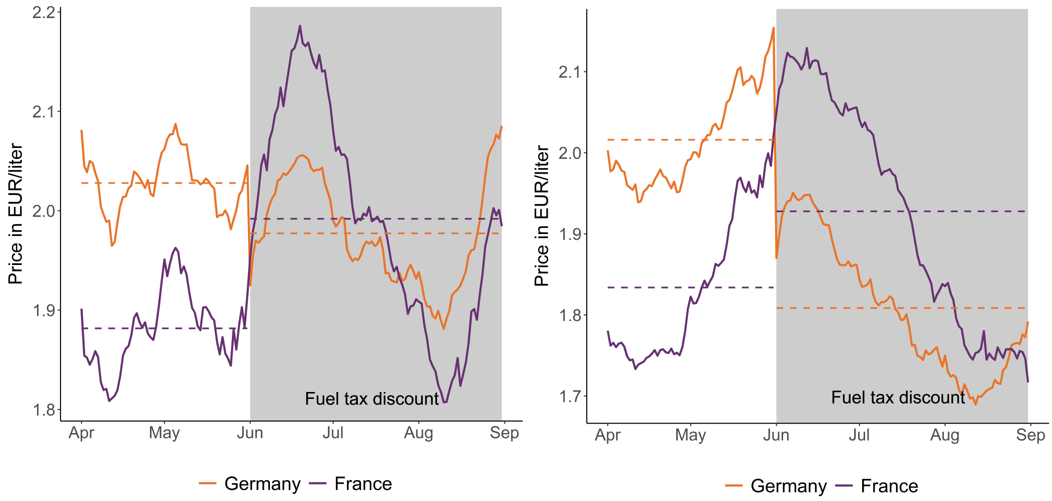
[9] We use absolute prices rather than logarithmic prices because they are easier to interpret and allow direct statements about the effectiveness of the FTD.

over time. Figure 3.1 shows the evolution of daily prices for both countries from April to the end of August 2022. The gray area marks the treatment period from June to August 2022, when the German Fuel Tax Discount was in effect. The dashed lines show the period averages. Before the FTD, prices peaked in May 2022 at around 2.09 Euros/liter for Germany (in orange) and around 1.96 Euros/liter for France (in purple). Overall, German diesel prices are consistently higher than French prices throughout the pre-treatment period.

A similar conclusion can be drawn for the evolution of E10 prices: In the pre-treatment period, on average, prices were lower in France than in Germany. Looking at the pre-treatment period trends, the graph for both diesel and E10 illustrates that prices in both countries moved similarly, providing some support for parallel trends. We also provide more formal support for the parallel trend assumption by applying the framework outlined by Rambachan and Roth (2023). The results are presented in Section 3.F of the appendix. We also show that the French price evolution is not different from the other European countries in Figure 3.E.3 in the appendix ruling out that our control group is special.

Right after the introduction of the German Fuel Tax Discount on June 1, 2022, gasoline prices dropped sharply, from 2.05 Euro per liter for diesel on the last day of May to 1.92 Euros per liter and from 2.15 to 1.87 Euros per liter for E10. Obviously, the tax discount was passed through to the consumers immediately after its introduction.

Figure 3.1: Average Daily Gasoline Prices for Diesel and Petrol (E10) in Germany and France



(**a**) Diesel (**b**) Petrol (E10)

Notes: The graph shows the average daily diesel (left panel) and E10 price (right panel) for Germany (in orange) and France (in purple). The gray area marks the introduction of the German Fuel Tax Discount, which lasted from June 1^{st}, 2022, to August 31^{st}, 2022. The dashed lines are the period averages.
Source: Authors' graph. Tankerkoenig provides the raw data for Germany and by Le Prix des Carburants for France.

3.4 Results

According to the estimation results originating from the difference-in-differences approach presented in Equation (3.6), the Fuel Tax Discount reduces the price of diesel by 16.1 Cents and the price of E10 by 30.3 Cents per liter. These price effects translate into pass-through rates of 96% and 86%, respectively, calculated using Equation (3.7). Diesel thus exhibits a higher pass-through rate, which is consistent with other findings in the literature (e.g., Schmerer and Hansen, 2023; Fuest et al., 2022).

The higher pass-through for diesel may be explained by differences in car ownership. Diesel cars, on average, have lower fuel consumption and higher mileage, making them ideal for commuting and business travel (see Federal Ministry for Digital and Transport, 2022). It may be that station owners want to attract this particular group of drivers and, therefore, overcompensate by transferring higher shares of the tax reduction.

Due to the technical advantages of diesel engines, drivers of diesel cars can also be labeled as frequent drivers, which equips them, from a theoretical viewpoint, with a lower price elasticity for fuel as they depend on affordable gas. A lower price elasticity results in higher pass-through rates according to Equation (3.5).[10]

To assess the economic relevance of the tax discount, we present the relative price reduction in terms of averages by comparing the estimated price effect with the average price levels in the post-treatment period. The estimated price changes correspond to significant price reductions of about 8% for diesel and 17% for E10, demonstrating the effectiveness of the Fuel Tax Discount in substantially alleviating the population's cost burden during the period of high energy prices.

3.4.1 Heterogeneities Across Space

While Table 3.1 reports the overall effect of the FTD, we are also interested in the spatial pattern. Figure 3.2 shows the regional differences at the county level for diesel (panel A) and petrol (panel B). Both maps show a distinct

[10]As argued before, this conclusion only holds under the condition of linear demand, which prevails here as shown in the auxiliary analysis in Section 3.A of the appendix.

Table 3.1: Estimation Results on the Pass-through of the Fuel Tax Discount from the Difference-in-Differences Approach

Dependent Variable:	Price of diesel/ petrol			
	OLS	Region FE	Time FE	Region & Time FE
	(1)	(2)	(3)	(4)
Diesel				
FTD × GER	-0.159^{***}	-0.160^{***}	-0.161^{***}	-0.161^{***}
	(0.001)	(0.000)	(0.001)	(0.000)
Petrol (E10)				
FTD × GER	-0.300^{***}	-0.302^{***}	-0.302^{***}	-0.303^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Pass-through				
Diesel	95.2%	95.8%	96.3%	96.3%
Petrol (E10)	85.3%	85.9%	85.9%	86.2%
Price reduction (in means)				
Diesel	8.0%	8.1%	8.1%	8.1%
Petrol (E10)	16.6%	16.7%	16.7%	16.8%
Fixed-effects				
Station		✓		✓
Date			✓	✓

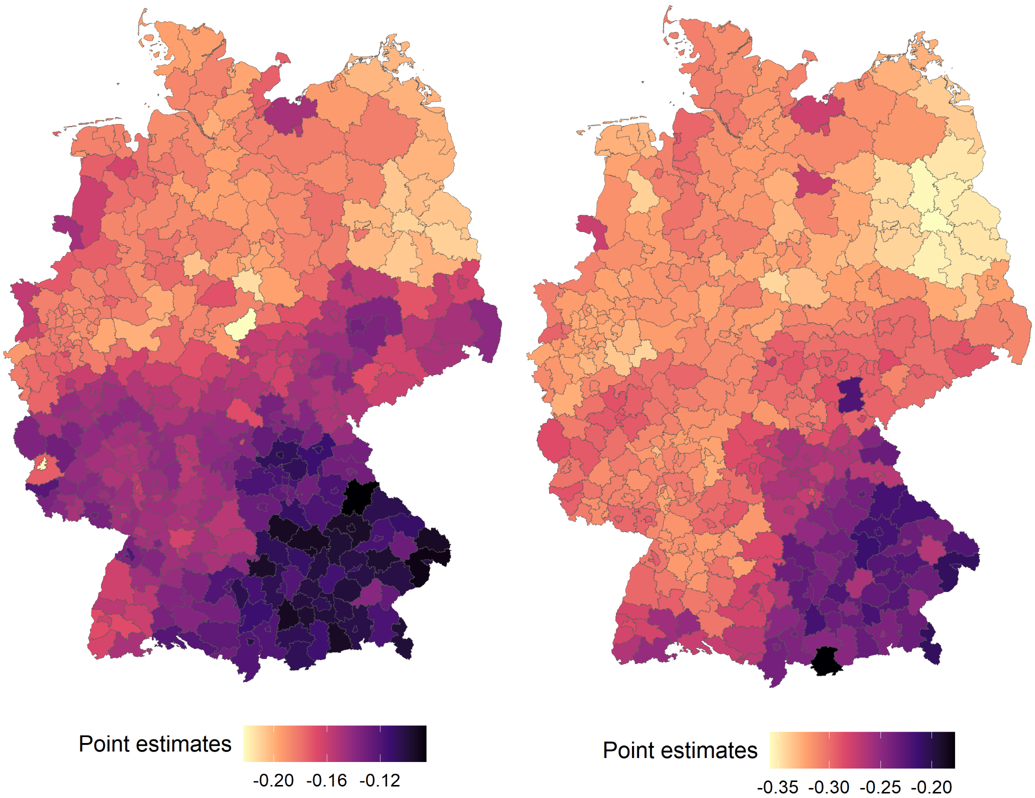
Notes: The table shows the baseline results and pass-through of the FTD with no fixed effects (column 1), regional fixed effects at station-level (column 2), time fixed effects at day-level (column 3), and regional and time fixed effects (column 4). Clustered standard errors at the station level are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

regional pattern with a wide range of price effects (about 14 Cents for diesel and about 18 Cents for E10). For both fuel types, there is a North-South divide: Counties in the South receive less of the tax discount than counties in the North, with counties in Bavaria showing particularly low pass-through rates. This finding may be correlated with regional economic conditions, such as income: Bavaria and Baden-Württemberg are among those federal states with high per-capita incomes.

The FTD benefits a broad range of people due to the distinct regional pattern. Table 3.B.3 in the appendix lists the number of people of working age per pass-through bracket, demonstrating the great range of pass-through rates for diesel (50% to 140%) and E10 (50% to 110%). While 15% and 35%

of the people can expect a full pass-through for diesel and E10, respectively, roughly 10% of the population only receives 50% of the FTP tax reductions. However, there is a significant portion of the working population receiving more than 100% pass-through due to overcompensation for diesel.

Figure 3.2: Regional Pass-Through Rates of the Fuel Tax Discount



(**a**) Diesel (**b**) Petrol (E10)

Notes: The figure shows the regional effects of the FTD as point estimates at the district level for diesel (left panel) and E10 (right panel). Darker colors indicate lower price effects, corresponding to lower pass-through rates.
Source: Authors' graph.

Spatial Heterogeneities and Competition

In addition to the overall pass-through of tax cuts, we also examine the impact of competition and the role of demand elasticity - the two key components in the pass-through formula (3.3).

First, we analyze various levels of competition by utilizing relative station density as a direct indicator of local fuel supply and, therefore, local competition. A small number of stations in a particular area implies that station operators can sell more without encountering significant competition.

We construct our station density measure by counting the number of gas stations per county.[11] To ensure an accurate measure of local supply and competition, we adjust the station density by the local car density at the municipality level. This is because a large number of stations does not necessarily indicate a large number of available cars. We use information provided by RWI-GEO-GRID (RWI, 2022), which lists the number of cars per household within a one square kilometer grid cell in 2020. We aggregate this data to the municipality level. The relative station density allows us to examine the setting of high and low levels of competition.[12]

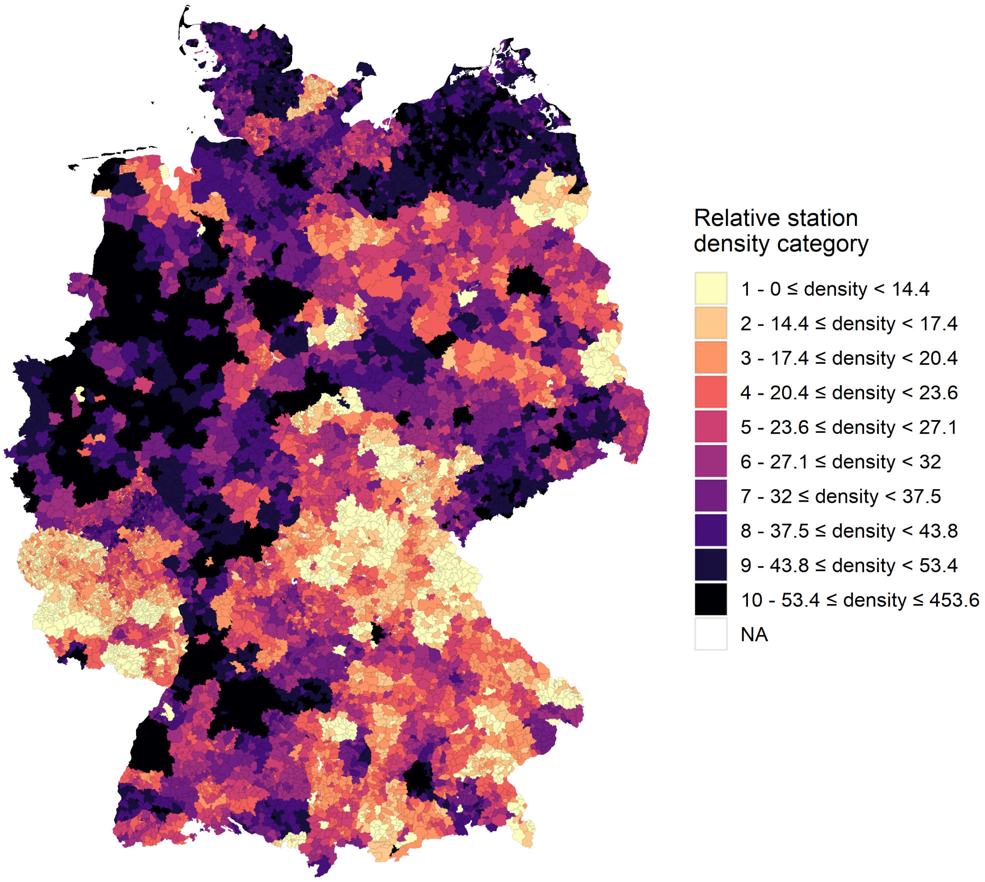
We divide the relative station density measure into groups based on deciles. The first group indicates areas of low competition. The 10^{th} group with high station density represents high competition regions. Figure 3.3 presents the deciles of the relative station density at the municipality level. The regional pattern shows high values in western Germany, particularly in North Rhine-Westphalia and Lower Saxony. High to medium values are also present in eastern Germany, specifically in Brandenburg and Mecklenburg-Western Pomerania. However, low values of our station density measure are observed in Rhineland-Palatinate, Bavaria, and partially in Thuringia.

After determining the relative station density at the municipality level, we assign the stations accordingly and repeat our analysis. We observe an increasing pass-through rate with increasing competition intensity for both fuel types (Figure 3.4). For the three least competitive groups, the pass-through rates are approximately 84% for diesel and 80% for petrol. These values are lower than our baseline result. On the other end of the spectrum, in highly competitive markets, the pass-through rates are about 100% for diesel and 89% for E10. The general trend of higher pass-through rates for diesel compared to E10 remains consistent in this scenario. As hypothesized by theory (see Section 3.2), the higher the competition level, the higher the

[11]We use the number of county gas stations because not all municipalities have their own gas station.

[12]The analysis relies on the assumption that drivers stay within their municipal boundaries to obtain fuel. This may be more true in less densely populated areas where the distance between stations may be greater, making trips to neighboring communities more costly (in terms of time and money). With higher population densities and more towns clustered together, this assumption may be less valid.

Figure 3.3: Deciles of Relative Station Density at the Municipality Level



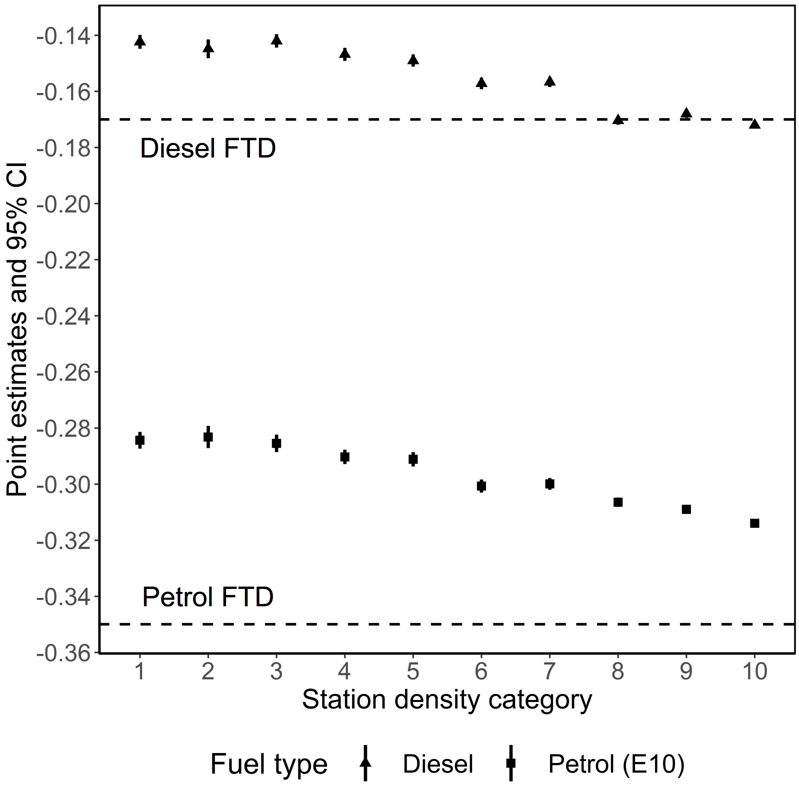
Notes: The map shows the categories (based on deciles) of relative station density at the municipality level, reflecting gas stations per car per household. Some municipalities have missing values as they are not populated.
Source: Authors' graph.

pass-through rate.

Spatial Heterogeneities and Demand Elasticity

In addition to the impact of competition, we are also interested in the second key component - the elasticity of demand (ϵ_D). As discussed in the theory section, we consider the demand elasticity to be fixed over time, but there are level differences between groups. Since ϵ_D is unknown and difficult to determine directly at the local level, we approximate it using local purchasing power per person, which is given by the RWI-GEO-GRID data set (RWI, 2022). We aggregate the given income data to the municipalities and determine the local income level for each station. A higher income category

Figure 3.4: Heterogeneity Results: Degree of Competition - Spatial Pattern



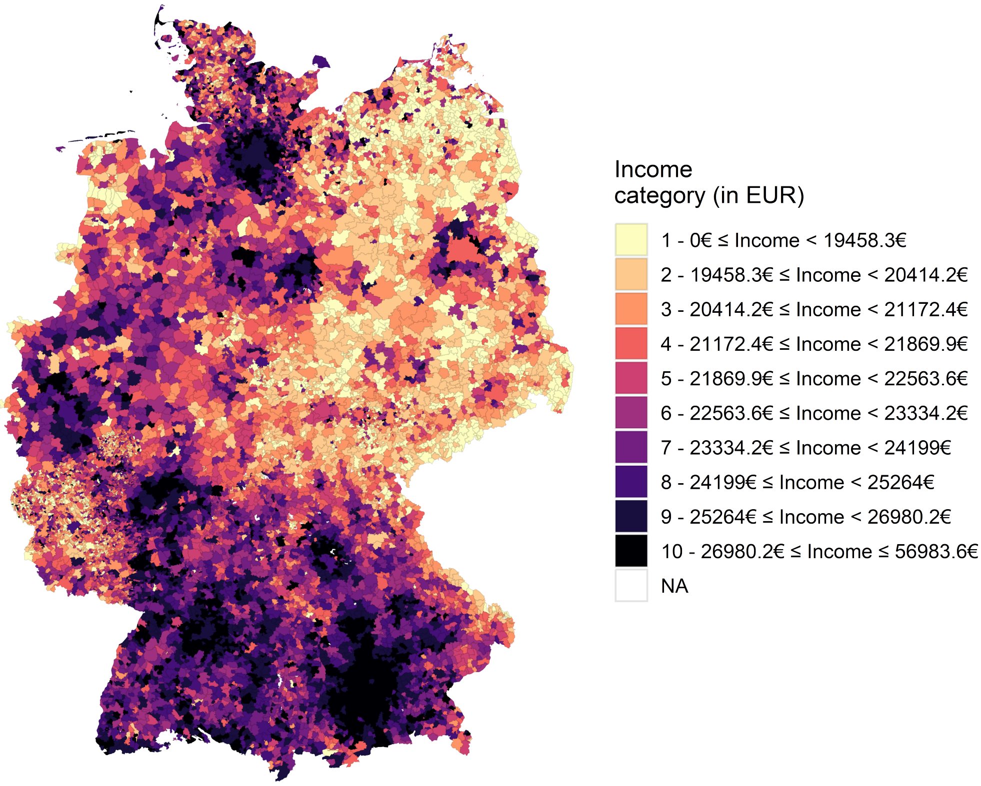
Notes: The graph shows the estimation results for various station density groups, indicating different levels of competition. Group 1 indicates low station density and low competition. Group 10 represents high station density and high competition levels. The dashed lines indicate the FTD levels (16.71 Cents for diesel and 35.16 Cents for E10).
Source: Authors' graph.

is associated with a higher degree of demand elasticity, resulting in lower pass-through.

Figure 3.5 gives an overview of the income levels of municipalities in Germany. The regional pattern suggests that the geographical south of Germany (including the states of Bavaria and Baden-Württemberg) is the wealthiest region. In particular, cities such as Munich and Stuttgart and their surrounding municipalities are highlighted on the map. Other cities, such as Hamburg in the north and Frankfurt am Main in the west, are also associated with higher incomes.

The regional pattern of the estimated effects for the ten income groups suggests a decline in pass-through rates from stations in low-income areas to

Figure 3.5: Income Categories at the Municipality Level

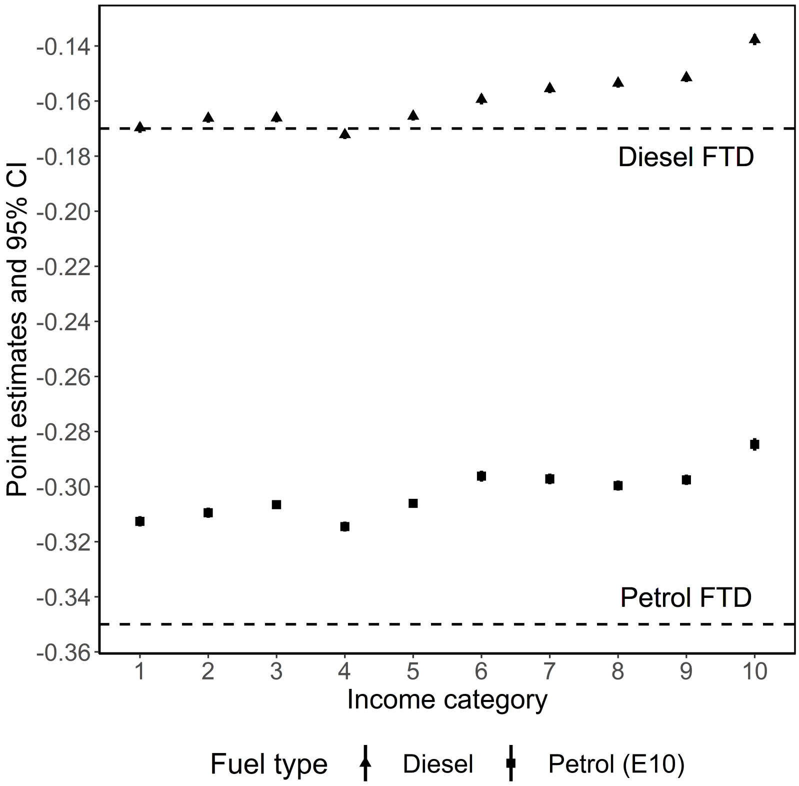


Notes: The map shows the income categories (based on deciles) for Germany at the municipality level. Some municipalities have missing values as they are not populated.
Source: Authors' graph. RWI (2022) provides the raw income data.

those in high-income areas, regardless of fuel type (Figure 3.6). While the first four income groups for diesel have perfect pass-through (around 100%), the highest income group can only benefit from a pass-through rate of 82%. The pattern is similar for E10. Again, we see the highest pass-through for stations in low-income regions. The first four groups indicate a pass-through between 88% and 89%. High-income regions show a pass-through rate of 81%. The findings support the regional pattern of the overall effect (see Figure 3.2).

These empirical results support our rationale that pass-through is lower in high-income areas because households in these areas are less dependent on tax cuts, and station operators can sell more expensive fuel without risking losing customers. It also confirms the theoretical notation that high demand elasticity leads to lower pass-through rates.

Figure 3.6: Heterogeneity Results: Degree of Demand Elasticity - Spatial Pattern



Notes: The graph shows the estimation results for various income groups indicating different degrees of demand elasticity. Group 1 represents low-income regions, while Group 10 represents high-income regions.
Source: Authors' graph.

3.4.2 Heterogeneities Across Time

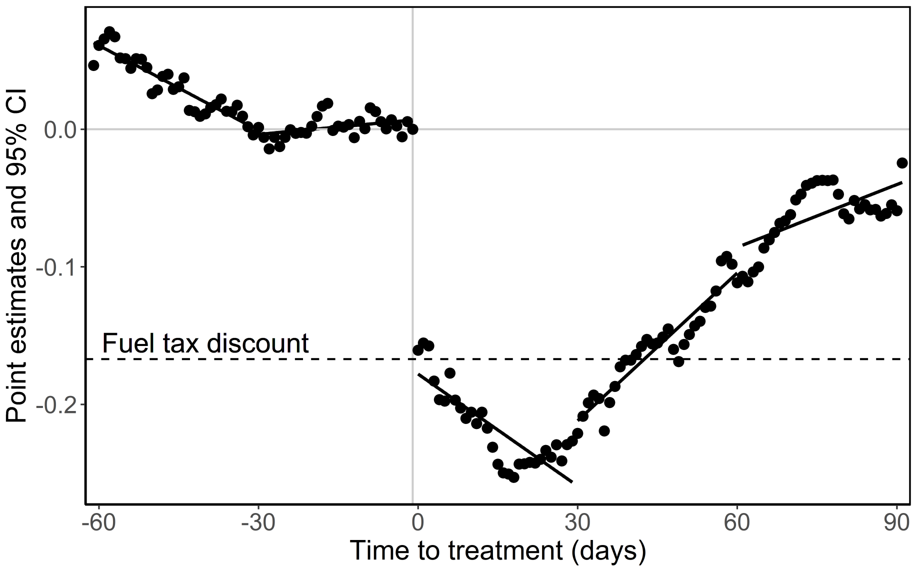
While previous analyses highlight the spatial pattern, we are also interested in the temporal pattern and whether the pass-through rate changes during the policy intervention. Figure 3.7 and Figure 3.8 show our baseline results for diesel and E10 over time. Both figures show the price effect with respect to May 31st, the last day before the introduction of the FTD.[13] The black solid lines show the monthly trend, and the dashed lines show the magnitude of the price discount (16.71 Cents for diesel and 35.16 Cents for E10).

We find an immediate decrease in diesel prices with the implementation of the FTD. On June 1st, the price falls by 16.1 Cents per liter, which corre-

[13]Confidence intervals are not visible because the standard errors are typically around 0.001. The coefficients are, therefore, precisely estimated.

sponds to a pass-through rate of 96.3%, identical to our overall result. The next two days remain at the same pass-through level. After this initially stable period, the pass-through rate increases to 151.4% 18 days after the introduction of the FTD. This means that gas station operators have passed on much higher rates to consumers than the law requires. This overcompensation is reversed in the next period of about 20 days, where the price reduction again approaches perfect pass-through (about 100%). From then on, operators pass on less and less of the tax reduction to the consumer over time. 60 days after the implementation of the FTD, the pass-through rate is only 67%. At the end of the policy instrument (August 31^{st}), the price reduction is only 2.4 Cents per liter or a pass-through of 14.4%.

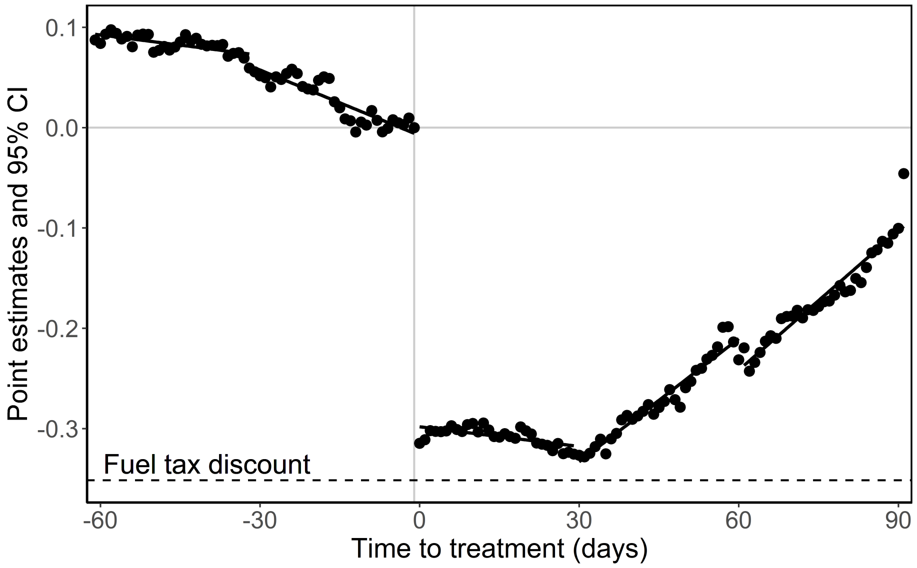
Figure 3.7: Estimation Results: Temporal Pattern for Diesel



Notes: The figure shows the point estimates and the 95% confidence intervals (CI) for diesel over time with respect to May 31^{st}, the last day before the introduction of the FTD. The black solid lines indicate the monthly trend, and the dashed line represents the magnitude of the price discount (16.71 Cents per liter).
Source: Authors' graph.

The pattern for E10 is similar. With the introduction of the FTD (35.16 Cents per liter for E10), the price decreased by 31.5 Cents, which corresponds to a pass-through of about 89.6%. During the first month of the tax reduction, the price decrease is relatively stable (between 86% and 93% pass-through). There is no overcompensation as in the case of diesel. After 30 days, we see a similar pattern to that of diesel. Retailers pass on less of the tax reduction over time. At the 60-day threshold, the price reduction is 23 Cents (65.7% pass-through). On the 80^{th} day, we observe only 46.6% pass-through, and on the last day it drops to 14.4%.

Figure 3.8: Estimation Results: Temporal Pattern for Petrol



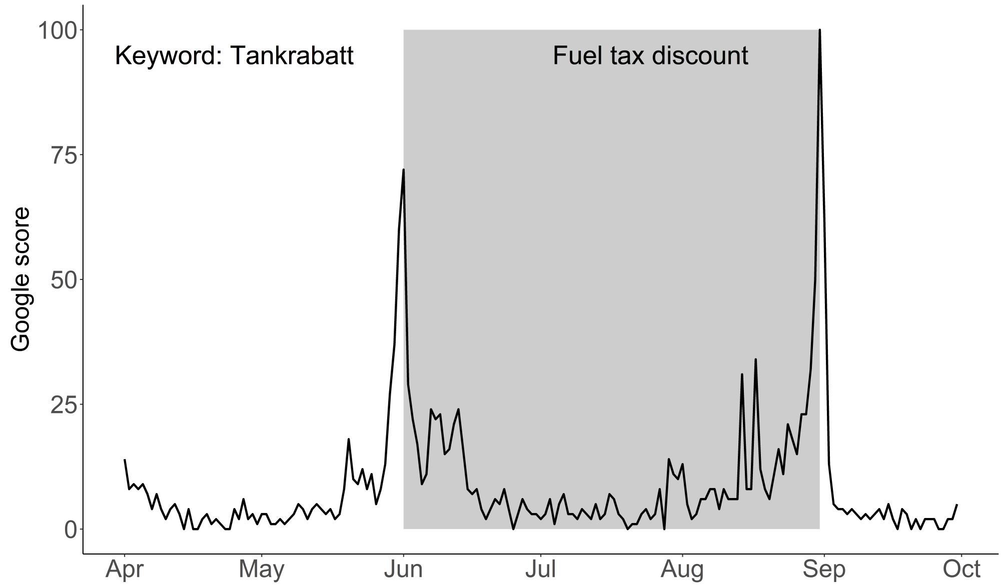
Notes: The figure shows the point estimates and the 95% confidence intervals (CI) for E10 over time with respect to May 31^{st}, the last day before the introduction of the FTD. The black solid lines indicate the monthly trend, and the dashed line represents the magnitude of the price discount (35.16 Cents per liter).
Source: Authors' graph.

A possible explanation for the high pass-through and especially the overcompensation for diesel in June could be the high media attention. Many newspapers reported and speculated about whether the gas stations would pass on the FTD to the consumer or whether the tax reductions are a subsidy to the oil companies.[14] Public attention may have contributed to higher pass-through rates and seemingly greater competition among service providers. Figure 3.9 shows an analysis of Google trends for the keyword "Tankrabatt" (fuel discount). It shows that public interest with respect to this keyword was high, especially on June 1^{st} and August 31^{st}. In between, there is only moderate interest. The low pass-through rates at the end of August, despite

[14]See, for example, the online article in ZDF (2022) ("Streit über hohe Spritpreise: Verpufft der Tankrabatt?") on March 30^{th}, 2022 or Tagesschau (2022) ("Wie stark sinken die Spritpreise?") on June 1^{st}, 2022.

high media attention, can be attributed to the limited time frame of the FTD. The policy intervention was restricted to a period of three months. Therefore, non-compliance at the end was unlikely to be punished by public pressure.

Figure 3.9: Public Attention According to Google Trends



Notes: The figure shows the trend graph according to Google Trends for the keyword ”Tankrabatt” (fuel discount) for April 1^{st} to September 30^{th} 2022. The grey area marks the introduction of the German fuel discount, which lasted from June 1^{st} to August 31^{st}, 2022. The Google Score is defined as interest over time relative to the highest point in the observed period. A value of 100 represents the highest search popularity.
Source: Authors' graph. The raw data is based on Google Trends.

From a policymaker's perspective, the temporal baseline results show that the countermeasure against high fuel prices is only partially effective. At the beginning of the FTD, we observe high pass-through rates, corresponding to the high effectiveness of the policy instrument. Over time, the desired effect diminishes. Recalculating the pass-through rate to reflect this diminishing effect yields estimates of 70% for E10 and 86% for diesel, about 15 and 9 percentage points lower than the estimates that ignore this temporal pattern.

Temporal Heterogeneities and Competition

Again, we are interested in the impact of competition and examine the evolution of pass-through for high competition (i.e., high station density) and low competition (i.e., low station density) settings. We only report the results for the highest station density (high competition) [in orange] and the lowest station density (low competition) [in purple] in Figure 3.10.

The general pattern documented in the baseline setting is confirmed for both fuel types. We observe high pass-through rates at the beginning of the discount with overcompensation for diesel. Thereafter, the pass-through decreases steadily until the end of the discount. For the different station density groups, we see that the pass-through rates for the high station density group (high competition) are greater than for the low station density group (low competition), regardless of the fuel type. This confirms the finding in the literature that more competition leads to higher pass-through.

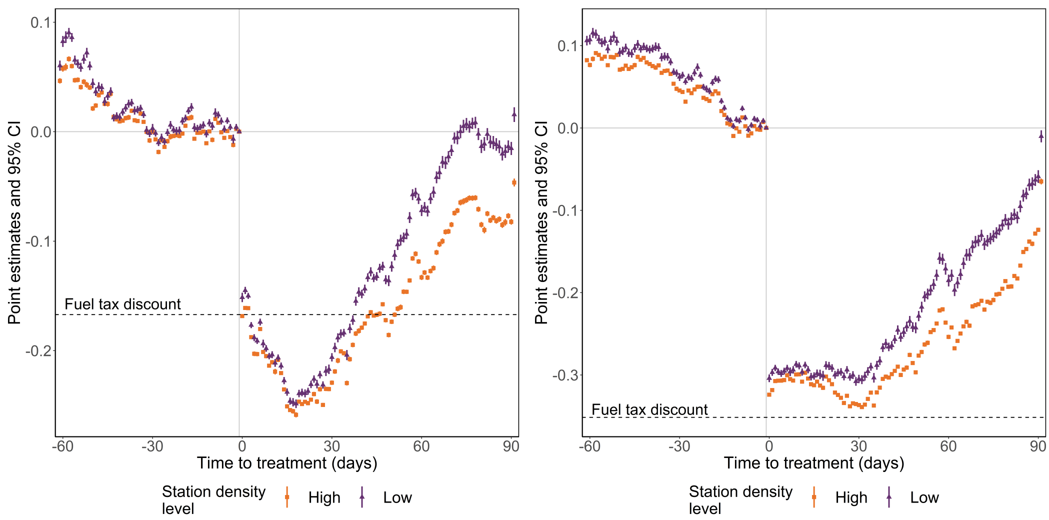
Figure 3.10 also shows a divergence between the two station density groups. The low station density group (low competition) diverges from the high station density group (high competition), indicating a faster path to lower pass-through rates. The divergence starts around day 30 for diesel and a bit earlier (around day 20) for petrol after the implementation of the FTD. It appears that stations in low-competition areas are less inclined to pass on the FTD and reduce the amount faster than stations in high-competition areas.

Temporal Heterogeneities and Demand Elasticity

As before, we also look at the temporal development for different demand elasticities. Figure 3.11 shows the trends over time for the highest and lowest income groups – our approximation of different levels of demand elasticity. Stations in high-income areas have lower pass-through rates than their counterparts in low-income areas. The pattern for diesel is less clear during the first 40 days of the FTD. Both groups are closely related and show the usual pattern of high pass-through rates with overcompensation. However, the stations in the high-income group typically show high pass-through rates, which is contrary to the intuition presented above. High income should signal high demand elasticity and, hence, a lower pass-through rate. The trend reverses on day 40 when high-income stations reduce their pass-through more than low-income stations. The values even drop to almost no pass-through around day 70.

For E10, we observe a clear distinction between stations in the two income groups. Retailers in high-income regions pass on less of the tax reduction

Figure 3.10: Heterogeneity Results: Degree of Competition - Temporal Pattern



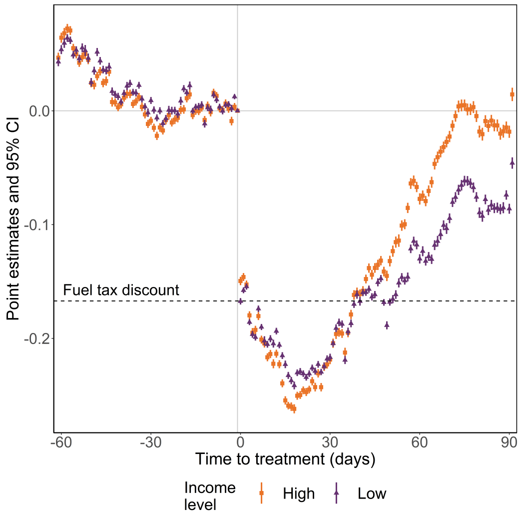
(**a**) Diesel (**b**) Petrol (E10)

Notes: The figure shows the point estimates and the 95% confidence intervals (CI) for the price effect of the FTD over time with respect to May 31^{st} for diesel (left panel) and E10 (right panel). The results are shown for high station density values (high competition) and low station density values (low competition). The dashed lines indicate the FTD levels (16.71 Cents for diesel and 35.16 Cents for E10).
Source: Authors' graph.

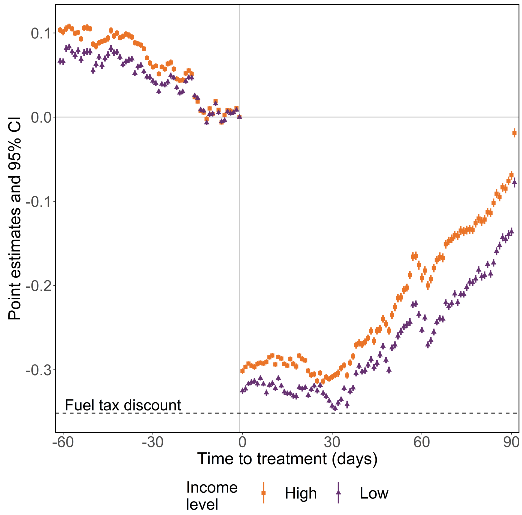
to consumers from the start. While the difference is about ten percentage points at the beginning of the FTD (e.g., 92% in low-income areas vs. 84% in high-income areas on day one), it increases to 18 percentage points on day 18 and 17 percentage points on the last day of the FTD.

Overall, the results for high- and low-income regions show that low-income areas are more likely to benefit from the implementation of the FTD. Although the degree of pass-through has decreased over time, stations in low-income regions pass-through more.

Figure 3.11: Heterogeneity Results: Degree of Demand Elasticity - Temporal Pattern



(a) Diesel



(b) Petrol (E10)

Notes: The figure shows the point estimates and the 95% confidence intervals (CI) for the price effect of the FTD over time with respect to May 31st for diesel (left panel) and E10 (right panel). The results are shown for low-income and high-income areas. The dashed lines indicate the FTD levels (16.71 Cents for diesel and 35.16 Cents for E10).
Source: Authors' graph.

3.5 Conclusion

This paper investigates the relationship between pass-through and competition, as well as demand elasticity approximated by regional income. We use the introduction of the fuel discount in Germany as a quasi-experimental setting and combine it with daily station-level price data to examine whether and how long the tax cuts were passed on to consumers. We also shed light on the role of competition and the impact of income-related demand elasticities.

Our results suggest that the FTD was passed on immediately after its introduction but the pass-through rates differ spatially. Further, the pass-through declined rapidly over time, a pattern that could be explained by public attention increasing the pressure to lower prices, especially at the beginning of the intervention. Evidence from Google Trends suggests, however, that as this attention waned, so too did the pass-through rate. With respect to competition, we show that high competition leads to higher pass-through rates. The temporal pattern established in the baseline is maintained. Furthermore, our results suggest that low demand elasticity represented by low-income groups leads to higher pass-through, which is consistent with microeconomic intuition, but, to our knowledge, has not been documented extensively empirically yet.

From a policy perspective, our study shows that the Fuel Tax Discount was largely passed on to the customer, especially at the beginning of the instrument. However, the effectiveness decreased over time. The discussion of demand elasticity and income suggests higher pass-through rates for low-income regions, but the time trend of declining effectiveness remains.

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Appendix

3.A Testing for Convexity of Demand

Table 3.A.1: Demand Curvature: Logarithmic Specification

Dependent Variable:	log(Monthly km driven)	log(Monthly km driven)	log(Monthly fuel consumption)	log(Monthly fuel consumption)
	(1)	(2)	(3)	(4)
Log(fuel price)	−0.371**	−0.202	−0.299*	−0.285
	(0.180)	(0.243)	(0.177)	(0.244)
Log(fuel price sq.)		−0.322		−0.027
		(0.386)		(0.396)
Log(fuel price) × diesel	0.386**	0.315	0.417**	0.411**
	(0.179)	(0.193)	(0.173)	(0.189)
Constant	6.704***	6.688***	3.696***	3.695***
	(0.132)	(0.132)	(0.148)	(0.148)
Observations	10,856	10,856	10,856	10,856
R^2	0.729	0.729	0.717	0.717

Notes: The table shows the estimation of the demand convexity using the German Mobility Panel and a logarithmic model specification. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

Table 3.A.2: Demand Curvature: Linear Specification

Dependent Variable:	Monthly km driven	Monthly km driven	Monthly fuel consumption	Monthly fuel consumption
	(1)	(2)	(3)	(4)
Fuel price	−265.489*	−553.623	−13.796	−59.634
	(137.166)	(937.454)	(10.443)	(72.469)
Fuel price sq.		102.184		16.256
		(332.102)		(25.636)
Fuel price diesel	393.416***	428.746**	28.611***	34.232**
	(148.383)	(184.489)	(10.512)	(13.728)
Constant	1231.724***	1432.582**	50.331***	82.285
	(228.211)	(682.677)	(18.095)	(52.980)
Observations	10,856	10,856	10,856	10,856
R^2	0.717	0.717	0.703	0.703

Notes: The table shows the estimation of the demand convexity using the German Mobility Panel and a linear model specification. Robust standard errors are in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Authors' table.

3.B Population per Pass-Through Bracket

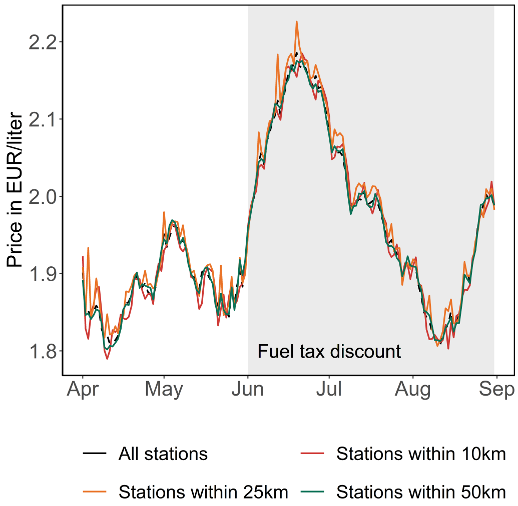
Table 3.B.3: Population per Pass-Through Bracket

	Working population (aged 15-64 years)	
Pass-through brackets (in %)	Based on diesel	Based on petrol (E10)
	(1)	(2)
(50,60]	1,580,815 (2.94%)	246,984 (0.46%)
(60,70]	3,848,005 (7.16%)	4,875,372 (9.07%)
(70,80]	3,776,798 (7.02%)	4,312,098 (8.02%)
(80,90]	11,051,571 (20.55%)	22,901,111 (42.59%)
(90,100]	7,903,237 (14.70%)	18,625,029 (34.64%)
(100,110]	9,851,017 (18.32%)	2,808,963 (5.22%)
(110,120]	11,697,282 (21.75%)	-
(120,130]	3,920,622 (7.29%)	-
(130,140]	140,209 (0.26%)	-
Total	53,769,556 (100.00%)	53,769,556 (100.00%)

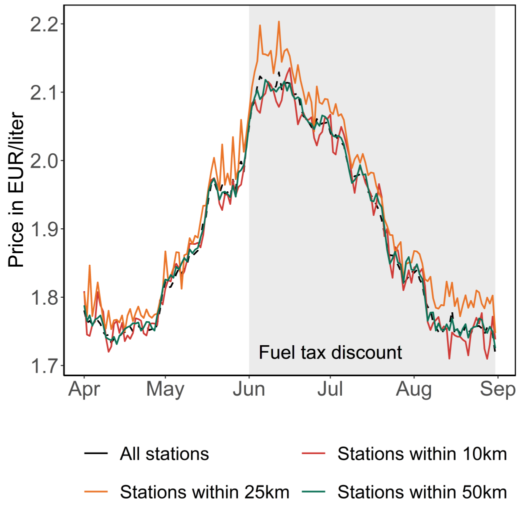
Notes: The table shows the number of people of working age (15-64 years) per pass-through bracket (in %) based on the regional estimates for diesel in column (1) and for petrol in column (2). The numbers in brackets below represent the percentage share of the affected working population.
Source: Authors' table.

3.C French Fuel Prices at the German Border

Figure 3.C.1: French Fuel Prices Close to the Border



(a) Diesel

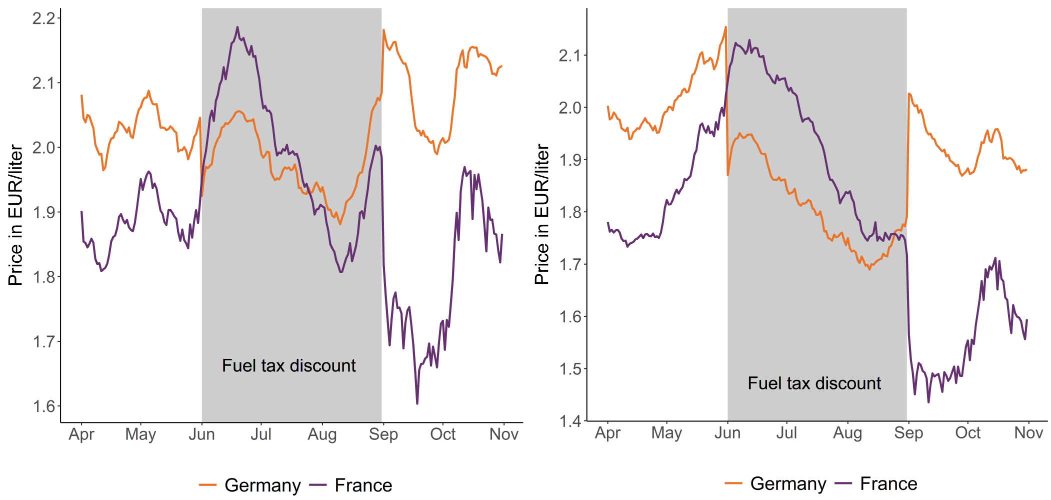


(b) Petrol (E10)

Notes: The figure shows the evolution of French fuel prices for diesel (left panel) and petrol (right panel) for all stations and for stations within 10 km, 25 km, or 50 km from the French-German border.
Source: Authors' graph.

3.D Development of Fuel Prices August-October 2022

Figure 3.D.2: Development of Fuel Prices Until October 2022



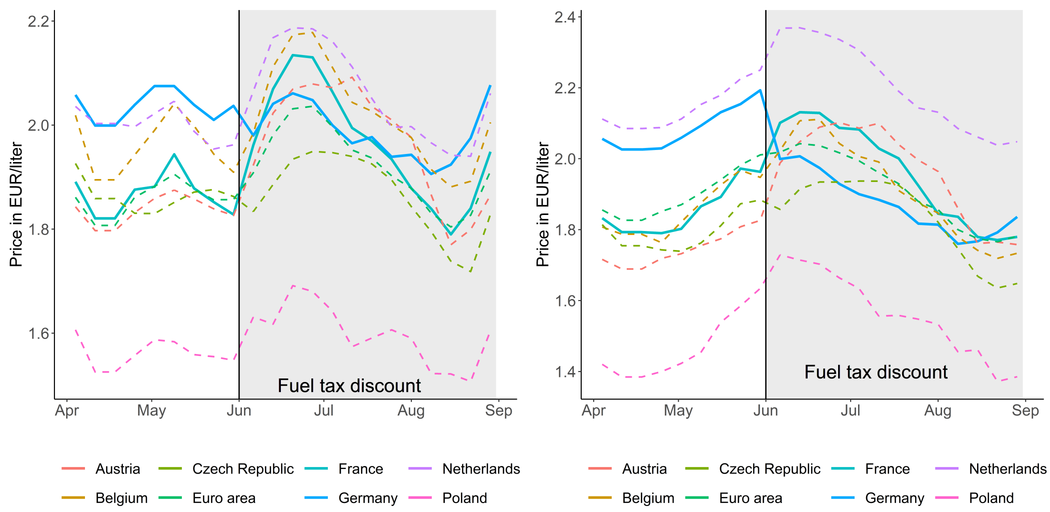
(a) Diesel

(b) Petrol (E10)

Notes: The graph shows the average daily diesel price for Germany (in orange) and France (in purple) until October 2022. The gray area marks the introduction of the German gasoline discount, which lasted from June 1^{st}, 2022, to August 31^{st}, 2022.
Source: Authors' graph. Tankerkoenig provides the raw data for Germany and Le Prix des Carburants for France.

3.E Fuel Prices in Europe

Figure 3.E.3: Fuel Prices in Europe



(a) Diesel **(b)** Petrol (E10)

Notes: The figure shows the weekly evolution of fuel prices for selected countries in Europe for diesel (left panel) and petrol (right panel).
Source: Authors' graph.

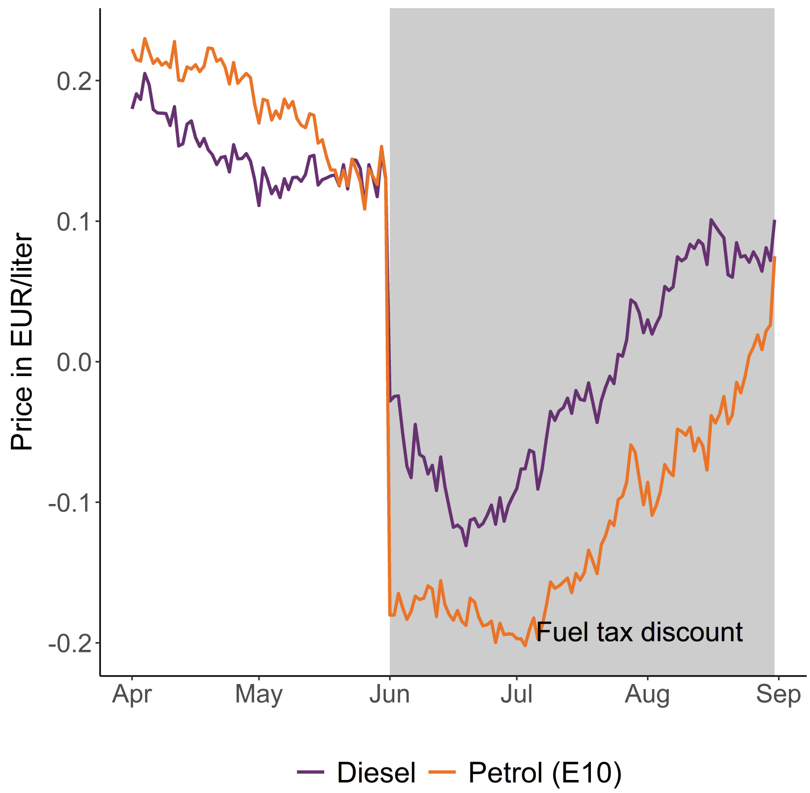
3.F Testing for Parallel Trends

This section provides additional support for the parallel trend assumption. Figure 3.1 and Figure 3.F.4 provide visual evidence of this assumption by plotting the price trends and price differences for Germany and France over time. These descriptive graphs show that the parallel trend assumption holds, especially close to the implementation date of the FTD (June 1^{st}), as both countries have similar price patterns. However, since these figures are only a visual aid in assessing parallel trends, we provide a more formal check by applying the framework recently outlined by Rambachan and Roth (2023). By imposing restrictions on the model, the authors ask how far the parallel assumption can be violated to still obtain significant estimates that can be interpreted causally. This provides an opportunity to perform a sensitivity analysis of our results. We focus on the days immediately following the introduction of the FTD.

Rambachan and Roth (2023) discuss mainly two restrictions for analyzing the parallel trend patterns - the relative magnitude restriction and the smoothness restriction. Which one to apply depends on the empirical setting. The relative magnitudes restriction, which is also discussed by Manski and Pepper (2018), assumes that the confounding factors that violate the parallel trend assumption are relatively constant between the pre-treatment and post-treatment periods. The smoothness restriction is the appropriate choice when the confounding factors arise from secular trends, i.e., it emphasizes prevailing (long-run) differences between the treated and comparison groups. The first constraint, relative magnitudes, seems more relevant to our setting for two reasons: First, we examine a short period of five months. Even though we include the entire period of the FTD, it is unlikely that France and Germany were put on completely different paths during this limited time. Second, and relatedly, we do not assume that confounding factors, i.e., (unobserved) differences between the two countries, are much stronger in the post-treatment periods than in the pre-treatment periods.

The relative magnitude constraint assumes that the maximum violation of parallel trends in the post-treatment periods equals the maximum violation of parallel trends in the pre-treatment periods times some parameter $\bar{M}$. This allows us to perform a sensitivity analysis for a sequence of $\bar{M}$ ranging from

Figure 3.F.4: Fuel Price Differences Between Germany and France



Notes: The figure shows the fuel price difference between Germany and France for diesel (purple) and E10 (orange). The grey area marks the introduction of the German fuel discount, which lasted from June 1^{st} to August 31^{st}, 2022.
Source: Authors' graph.

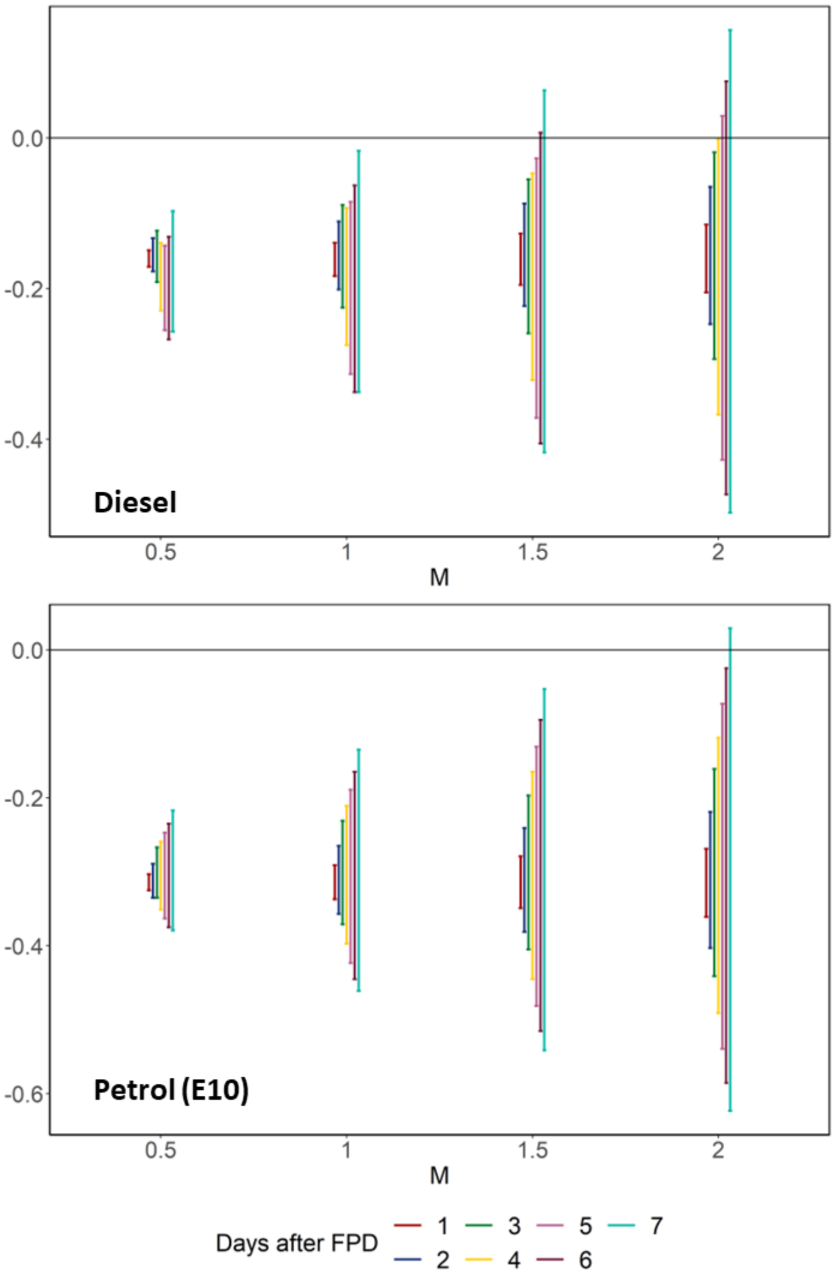
0.5 to 2.[15] Note that $\bar{M} = 0$ represents the originally estimated coefficient, which assumes that there are no parallel trend violations.

Figure 3.F.5 shows the implementation of the Rambachan and Roth (2023) framework for the days immediately following the FTD, the most important period where we want to rule out any bias. The figure shows that for diesel, all periods hold up to a factor of $\bar{M} = 1$. The parameter is even higher for E10, where all periods are robust to parallel trend violations for a factor of $\bar{M} = 1.5$. The wider confidence intervals with increasing $\bar{M}$ follow directly from the framework since increasing $\bar{M}$ implies a stronger violation of parallel trends, which leads to a less precise estimation of the coefficients.

[15]The interpretation of, for example, $\bar{M} = 2$ is that the violations of parallel trends in the post-treatment period cannot be greater than twice the violations in the pre-treatment periods in order to still obtain significant results.

Sensitivity analysis also allows us to establish a breakdown point. A threshold up to which we can assume robust results. The breakdown value for diesel for all periods is between $\bar{M} = 1$ and $\bar{M} = 1.5$ and for E10 between $\bar{M} = 1.5$ and $\bar{M} = 2$. Interestingly, the estimates for E10 are more robust to violations of parallel trends than the diesel coefficients. The graphical inspection of the price evolution suggests the opposite.

Figure 3.F.5: Robust Parallel Trends



Notes: The figure shows the outcome of the Honest-DiD approach (Rambachan and Roth, 2023) around the implementation of the FTD.
Source: Authors' graph.

Concluding Remarks

In this thesis, I investigate how preferences and decision-making in the spatial dimension result in heterogeneities in estimated effects. In a collection of three chapters, I examine (I) the impact of a law change that reduced railroad noise levels in the freight train sector on house prices at close proximity to the tracks, (II) the effect of the COVID-19 pandemic on housing prices through the paralysis it caused in the aviation sector, (III) the role of competition and demand elasticities in the German fuel market and how the given market structure influences the pass-through of the Fuel Tax Discount (FTD).

In the first chapter, I utilize the implementation of the Railroad Noise Protection Act (RNPA), which bans loud freight trains from the German railroad system by the end of 2020. This measure aims to reduce the environmental noise levels for people living near the tracks. I find that the noise reductions resulting from the RNPA are evaluated positively and lead to an increase in prices of noise-treated houses from 0.5% to 6.9%. The heterogeneity analysis shows that the value gained decreases with distance from the tracks. Therefore, the neighborhoods that benefit the most from the establishment of the RNPA are those with the highest noise levels. However, the analysis also reveals that the largest estimated effects occur in areas with generally high noise levels, not just those caused by railroad traffic. Further research is needed to understand the explanatory channel in these locations with street, airport, industrial, and railroad noise.

The second chapter examines the impact of the COVID-19 pandemic on air traffic and the resulting reduction in aircraft-related noise in Germany. The chapter is closely related to the understanding presented in Chapter 1. The study reveals that a decrease in environmental noise is associated with an increase in apartment prices of 2.3%. Furthermore, the research demonstrates that these positive effects continue to increase during the pandemic, with peaks of 6%. The observed effects only decay in 2022. While the early price gains at the beginning of the pandemic can be attributed to the improvements with respect to aircraft noise, the later effects require a different explanation. One potential narrative is information asymmetry between buyers and sellers, where interested buyers may not be able to adequately assess the local conditions and end up paying a price premium for seemingly quiet neighborhoods. Another explanation may be future expectations regarding air traffic. Possible future developments, such as an increase in online meetings and efforts to limit CO_2 emissions, may lead to a reduction in the number of planes and, consequently, lower noise levels. Further research may provide more information on these potential developments and their causes.

Lastly, Chapter 3 studies the Fuel Tax Discount (FTD) as a tool to investigate how the pass-through of a tax cut works in the German gasoline market. The FTD was introduced in Germany during the summer of 2022 and resulted in a significant reduction in fuel prices for a three-month period. We find that the pass-through rates are affected by the (local) level of competition and the prevailing degree of demand elasticity. There is also significant variation in pass-through rates across different locations and time periods. Surprisingly, the pass-through of the FPD diminishes drastically over time. Although there is almost complete pass-through at the beginning, the positive impact of the policy instrument becomes negligible towards the end. This finding raises questions about the overall effectiveness of the FTD.

Taken together, this thesis demonstrates the impact of events and policy interventions on local neighborhoods and their living standards. All three chapters show that although the applied settings are considered national strategies, they result in great heterogeneity in space and time at the local level. It is evident that assessing the impact and effectiveness requires high-resolution data to draw appropriate conclusions.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the author utilized *deepl.com/write* to enhance language and readability. After utilizing this tool, the author reviewed and edited the content as necessary and assumes full responsibility for its accuracy.

Erklärung

gemäß §10 Abs. 6 der Promotionsordnung der Mercator School of Management, Fakultät für Betriebswirtschaftslehre der Universität Duisburg-Essen, vom 11. Juni 2012.

Hiermit versichere ich, dass ich die vorliegende Dissertation selbständig und ohne unerlaubte Hilfe angefertigt und andere als die in der Dissertation angegebenen Hilfsmittel nicht benutzt habe. Alle Stellen, die wörtlich oder sinngemäß aus anderen Schriften entnommen sind, habe ich als solche kenntlich gemacht.

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Patrick Thiel

DOI: 10.17185/duepublico/81877
URN: urn:nbn:de:hbz:465-20240503-143405-7