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Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

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Patrick Thiel[1]

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Abstract

In 2017, the German federal government passed the Railroad Noise Protection Act to reduce the noise emitted by freight trains. This paper evaluates the effects of this law on house prices by using regional variation comparing affected homes close to train tracks and homes in greater distance before and after the introduction of the national strategy. The difference-in-difference framework suggests an increase in house prices by 0.5% to 2.5% for houses close to the tracks considering different time periods for the act being passed and its complete implementation. A heterogeneity analysis reveals increasing effects with reduced distance to tracks. It also shows that those with the highest general noise burden gain the most from the Railroad Noise Protection Act.

JEL-Codes: O18, Q53

Keywords: House prices; hedonic price function; railroad noise; Railroad Noise Protection Act

October 2022

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1 Introduction

Noise pollution is a major concern for many people, and the transportation sector is one of its biggest contributors. Living close to transportation infrastructure provokes regular complaints about the additional burden caused by noise and air pollution despite the facilitated access to the infrastructure network. High levels of environmental noise are not only disturbing but are also associated with health risks (see, for example, Babisch et al., 2005; Münzel et al., 2014; Vienneau et al., 2015). Permanent extensive noise exposure can be related to general cardiovascular diseases, specifically high blood pressure, and higher heart rates, as well as detrimental effects on sleep quality and, thus, its impact on cognitive abilities. Beyond these effects on health and mental wellness, noise also impacts residential quality as it represents a burden such as general disturbance.

Quantifying the influence of noise, a non-market good, is challenging. Information on health status and general satisfaction of people living close to tracks are not broadly accessible. Such direct measures may also be highly subjective. Additionally, available data usually does not match the small-scale level desired for an impact evaluation. Confronted with these challenges, hedonic estimations based on housing prices are widely used tools to evaluate the impact of non-market goods.

In this study, the focus lies on the evaluation of railroad noise as one of the major noise sources. I exploit the noise reduction induced by the Railroad Noise Protection Act (RNPA) to investigate the impact of the proximity to railroad tracks on house prices. The German federal government passed this law in 2017 because of the detrimental consequences of high noise levels caused by trains. It bans freight trains with outdated brake systems from German railroads by 2020 to tackle the noise burden close to tracks. Switching from the older system, cast-iron brakes, to the newer solution of composite brakes (so-called whisper brakes) can amount to a difference in noise levels of up to 10 decibels (dB) (Deutsche Bahn AG, 2021). The study aims at understanding the preferences for specific residential locations under changing environmental noise levels and, thus, allows for an evaluation of the effects of railroad noise on house prices.

The RNPA has the advantage that it applies to all regions of Germany which are exposed to railroad noise caused by freight trains. Other countermeasures intending to reduce noise levels, like subsidizing the modernization of exposed buildings or installing noise barriers, are highly local and partially selective. Not everybody is entitled to such funding as it depends on the building's condition. Furthermore, the process of applying for funding is bureaucratic and requires a justification of necessity. The RNPA shifts the responsibility to the noise producer and provides a novel setting for a broad noise reduction targeted at all residents close to the noise source, independent of their region

and social background.

Literature analyzing the effect of railroad-related noise on real estate prices in other regions typically finds a negative effect. Theebe (2004), for example, studies traffic noise in the Western part of the Netherlands and identifies a negative relationship between noise and house prices. Andersson et al. (2010) adds to this result by looking at road and railroad noise in Sweden and finding a negative impact on housing prices of 0.4% per decibel increase in railroad-related noise. Other regions include Norway (Strand and Vågnes, 2001) and South Korea (Chang and Kim, 2013). They find that a greater distance to railroad tracks is associated with higher house prices and that increases in noise diminish home values. Ahlfeldt et al. (2019) focus on land price capitalization effects by considering access to and noise emitted by Berlin's urban railroad system. They are also interested in the change of these effects over time as they employ data across the 20th century. Their findings suggest that people value access to the railroads and silence more over time as they become richer.

Of course, railroads are not the only studied noise source. Airports are another prominent topic in this strand of literature. The meta-analysis by Nelson (2004) shows a negative relationship between air traffic noise and property prices. Similarly, Jud and Winkler (2006), Cohen and Coughlin (2008, 2009) and Boes and Nüesch (2011) point in the same negative direction. Ahlfeldt and Maennig (2015) discuss differences in preferences regarding such disamenities.

Another strand of literature approaches the proximity to noise sources by focusing on accessibility. Being close to railroad tracks does come with the downside of noise exposure. But vicinity is also attributed to the advantage of having immediate access to railroad-related services. The literature has shown that this accessibility premium can impact housing prices positively. Examples include Brandt and Maennig (2012) analyzing railroad access in Hamburg (Germany), Dubé et al. (2013) focusing on openings of commuter rail stations in Canada, Bowes and Ihlanfeldt (2001) aiming at disentangling different channels concerning the accessibility aspect, the meta-study of Debrezion et al. (2007), and Debrezion et al. (2011), who investigate the quality of railroad services explicitly at stations in the Netherlands. Due to the importance of access, it is crucial to account for it in the analysis.

This paper contributes to the existing literature in the following ways. First, many studies concentrate on a limited regional area (e.g. on one specific city). This can often be attributed to the lack of data. Typically, geographically referenced railroad tracks are unavailable, or the corresponding housing data is missing. This study uses the geographic locations of all six major railroad corridors for freight traffic in Germany and links them

with precisely geographically-referenced housing units.

Second, this paper offers insights into the effectiveness of a tangible policy intervention to fight noise pollution cohesively. Other measures, for instance, noise barriers, focus solely on mitigating the consequences of extensive noise exposure. They are not preventing noise production in the first place, and hence, they only improve the situation for a limited number of people. This paper contributes to noise literature by showing that implementing a national strategy to counter high noise levels can lead to improvements for affected residents. I show that house prices are positively affected once the RNPA is introduced. Thus, this study also demonstrates a symmetry of effects with respect to the noise literature, which typically finds a negative noise effect on home prices. Additionally, relying on the RNPA adds the advantage of simultaneous treatment. There is no endogeneity in the assignment procedure as all residents in the treatment group (i.e., those close to the tracks), independent of social background and location, benefit from the implementation of the RNPA at the same time.

Lastly, railroad noise is less studied than other sources like road noise. This is especially true for Germany, where the relationship between railroad noise and property values is understudied. To my knowledge, this is the first work studying railroad noise impacts on property values on a large scale for Germany, as other studies only consider limited regional areas like specific cities. Thus, I show that noise countermeasures are not solely important in urban regions.

I combine geographically-referenced homes with the geographical information of freight train corridors to estimate a hedonic price function using regional variation between those having to deal with noise (treatment group) and those that are not disturbed by freight train noise (control group). The baseline results suggest that house prices close to railroad tracks increase relative to homes further away after the RNPA was introduced. In fact, they increased by 0.5% during the adoption period (July 2017 to November 2020) and gained 2.5% when the RNPA was fully enacted (after December 2020).

The paper is structured as follows: Section 2 provides the background to the RNPA and its importance as a countermeasure for freight train noise. Section 3 describes the empirical strategy employed to estimate the impact of the RNPA as well as the used data sources, and it offers descriptive statistics. Section 4 shows the results of the baseline regression, describes several robustness checks applied to validate these baseline results, and discusses the effect under varying settings. Section 5 concludes.

2 Background

Railroads are an essential tool for the transportation of goods in Germany. In fact, around 18% of goods were shipped by train in 2020 (Federal Office of Statistics, 2021a). This makes railroads the second most important mode of transportation of goods after transport by truck. The importance of railroad transportation will likely increase to 25% by 2030, as German policymakers aim towards a more environmentally friendly transportation sector (Federal Ministry of Transport and Digital Infrastructure, 2020). The downside of increased freight traffic on railroads as an alternative to transport by truck is an intensified burden on people living close to these tracks. Drawing on the noise statistics by the Federal Railway Authority (FRA), around 6.7% of the German population is affected by at least some noise from railroads during the day. This number rises to 11.9% at night (FRA, 2020)[1].

The FRA installed measuring stations close to tracks to monitor passing trains and gain insights into train characteristics (FRA, 2022)[2]. Freight trains have an average transit exposure level[3] of 84dB and an average maximum noise level of 90dB. Compared to a normal conversation at 60dB (Center for Disease Control and Prevention, 2019), a freight train would be louder, on average, by 24dB (or up to 30dB for the maximum noise level). When considering noise differences, it is crucial to recognize that they are measured on a logarithmic scale. Therefore, the actual measured sound level is different from the perceived loudness. To make differences in sound levels more approachable, the rule of thumb is that an increase by 10dB means that the noise source is perceived twice as loud (Murphy & King, 2014). For the example of freight trains, the difference of 20dB to 30dB compared to a normal conversation means that the train is perceived four to eight times as loud.

To mitigate the burden of high levels of noise for people living close to tracks, the federal government passed the RNPA in July 2017. At its core, this law aims to ban loud freight trains starting in December 2020 (Federal Ministry of Justice, 2017). During the period between the law being passed (July 2017) and commenced (December 2020), the operators were required to modernize their trains by switching from cast-iron brakes to composite brakes, so-called whisper brakes. The disadvantage of cast-iron brakes is that

[1]Note that the threshold for noise nuisances is defined for day time at 55dB and 45dB at night time. So, the higher share of people affected at night can be partly attributed to the lower detection threshold. As the overall sound level at night is lower, it also makes sense that more people are affected since this is a particularly sensitive time.

[2]The FRA oversees 19 stations which cover around two-thirds of the freight train transport activity (FRA, 2022).

[3]The transit exposure level represents the average sound pressure level of a train passing a certain location (Isert & Lutzenberger, 2020).

they roughen the wheel's surface, resulting in more friction between the wheels and the tracks over time. This causes the train to be louder while driving and braking. Conversely, composite brakes maintain a smooth surface because they are made of a combination of materials like rubber, metal, and resin (Allianz pro Schiene, 2022) and thereby protect the wheel from damage leading to less noisy trains. The corresponding noise reduction using whisper brakes can amount to 10dB, which leads to a reduced perceived loudness by half (Deutsche Bahn AG, 2019). After December 2020, violations against the RNPA could be fined up to 50,000 Euros. Operators were, therefore, heavily incentivized to modernize their fleet by the end of 2020. I refer to the period July 2017 to November 2020 as the adoption period and the period after December 2020 as the actual treatment period throughout the paper.

Figure 1 offers descriptive evidence on the noise levels emitted by trains over time and for day and night periods using data from measuring stations of the FRA.

Figure 1: Development of noise levels over time

Notes: Average noise levels for day (6 am to 10 pm) and night periods (10 pm to 6 am) are measured in dB based on the Day-Evening-Night index. The vertical line marks the complete adoption of the RNPA in December 2020, after which loud freight trains were banned, and non-compliance could be fined (Federal Ministry of Justice, 2017). The horizontal lines represent the mean noise levels for day and night before and after the full 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.

Figure 1 shows a decrease in noise levels over time for both day and night. Comparing average levels before and after the RNPA was fully adopted (after December 2020) also reveals a reduction in noise by 2.2dB for the day and 2.6dB for night times (see horizontal lines). Additionally, after December 2020, the night level is clearly below the day level.

Previously, both levels were of similar magnitude.

Note that the observation period for these noise measurements in Figure 1 starts in April 2019. The period covered in the analysis (June 2013 to June 2021) is not fully included since the network of measuring stations was only implemented in 2019. Therefore, I assume that noise levels prior to April 2019 were at least on the same level as in the remainder of 2019. This seems reasonable as the Deutsche Bahn, Germany's largest single provider of railroad services, amplified its efforts to switch to whisper brakes after the RNPA was introduced. The Deutsche Bahn completed the modernization in 2020 (Deutsche Bahn AG, 2021).

Note that the development of noise levels might also be partially attributable to the Covid-19 pandemic, which overlaps with the observation period. It might be that noise levels dropped due to constraints on national and international trade, and limitations on travel and business activities. One might also argue that the reduction in average noise levels is caused by fewer trains, as operators might be reluctant to modernize their fleet. Figure 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.

[4]The average monthly number of freight trains is 54.7 trains (day) and 32.8 trains (night) before December 2020 and 57.9 trains (day) and 35.1 (night) afterward.

Figure 2: Average number of freight trains

Notes: The graph shows the average number of freight trains by month. The horizontal lines in grey show the trend for the respective noise level and period. The vertical line marks the complete adoption of the RNPA in December 2020. The chart corresponds directly to Figure 1.
Source: Author's graph. The data is given by the FRA (2022).

3 Empirical Strategy and Data

3.1 Empirical Strategy

To estimate the effect of noise reduction due to the adoption of the RNPA on house prices, I estimate a hedonic price function in the tradition of Rosen (1974). Following the underlying idea that the price of a house can be described by the combination of its characteristics and immediate environment, an implicit price is estimated. The methodology allows retrieving a measurement for the effectiveness of the RNPA and the induced noise reduction based on revealed preferences, because (dis-)amenities including noise levels are assumed to be captured in the housing price.

The baseline setting applies the following equation:

$$\begin{aligned} ln(y_{ijt}) = X_{ij}\beta + \gamma Buffer500_i + \delta(LawPassed_t \text{ x } Buffer500_i) + \\ \theta(LawInForce_t \text{ x } Buffer500_i) + Month_t + Grid_j + \epsilon_{ijt}, \end{aligned} \tag{1}$$

where $ln(y_{ijt})$ is the logarithm of the asking 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,

[5]The housing unit 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.

distances to other noise sources and accessibility variables (see Table 1 for an overview of the variables used and Table 2 for summary statistics). The variable $Buffer500_i$ indicates whether the house lies within 500m from the tracks, capturing the treatment group. The variable $LawPassed_t$ is an indicator variable equal to one for months between July 2017 and November 2020 (the adoption period). Similarly, the variable $LawInForce_t$ indicates the months between December 2020 to June 2021, referred to as the actual treatment period. Therefore, δ and θ represent the coefficients of interests, giving the additional effect on house prices for being within the 500m radius from the tracks relative to homes further away after the RNPA has been passed ($LawPassed_t$ x $Buffer500_i$) and after the law is fully in force ($LawInForce_t$ x $Buffer500_i$).

Splitting the treatment period into two time slots follows the intention to capture different treatment intensities. The RNPA was implemented in two stages: Starting with July 2017, train operators had time to update their fleet until December 2020. The noise level is supposed to drop steadily during the period of modernization. After the end of 2020 the law was in place, and non-compliance could be sanctioned. The noise levels should be lower than in the previous period (as indicated by Figure 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 being 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 contains time fixed effects on the year-month level ($Month_t$) and regional fixed effects on the 1 x 1 km-grid level ($Grid_j$). I thus control for effects that are constant over time for each grid as well as that are constant across grids. The fixed effects, especially, capture time-invariant neighborhood characteristics. Combined with the extensive list of control variables, I assume that I can isolate the effects of the noise reduction induced by the RNPA.

I perform several robustness checks to support the baseline results. First, I restrict the sample to observations within 3km from the tracks. The control group in this setting contains all houses above 500m and up to 3km. This setup makes the treatment and control group more alike. The baseline specification allows for greater distances up to the municipality border. Second, I exclude the 15 largest cities from the sample in a first step, and cities with at least $100,000$ citizens in a second step. The purpose of these different regional samples is to ensure that agglomeration areas do not drive the estimated effects in the baseline specification, as housing prices are generally higher in such places. A neutral

zone is defined by excluding all observations with a distance between 500m and 1,000m in the next robustness check. The effects are expected to be larger than the baseline as the treatment and control group are more distinct in this setting.

The second set of robustness checks adopts different regional fixed effects. Instead of grid-level fixed effects, zip-code regional fixed effects are incorporated. Next, I add a state-time trend to control for state-specific time effects. An important assumption for this kind of analysis is that the control and treatment group evolve similarly prior to the treatment (July 2017). I perform a pre-trend analysis to check for this assumption. I split the pre-treatment period into four periods of approximately the same length of 12 months[6] and apply the baseline regression equation once again. Together with Figure 4, which shows the development of house prices over time graphically, the analysis provides evidence that the pre-trend assumption holds. Next, I conduct a placebo regression where the sample is restricted to the control period (prior to July 2017), and the treatment time is shifted to the middle of the control period (starting July 2015). So, half of the observation period is assumed to be under treatment now. The effect is expected to be insignificant because the RNPA was implemented in 2017, and thus, there is no treatment yet.

I also implement additional robustness checks in the Appendix A. I first use all main railroads instead of relying only on freight train corridors to show that the RNPA functions as intended by reducing noise levels in the transportation sector. The observed effect should be blurred and hence smaller when adding non-transportation and mixed-used tracks. I also apply a leave-one-out estimation where each of the six freight train corridors is excluded once to rule out that one specific set of tracks drives the findings. Finally, I add the distance to noise barriers as an additional control variable to the model. One concern might be that the effect of the RNPA might be confused with the impact of other countermeasures against high noise levels. This test aims at removing the impact of these barriers.

3.2 Data and Descriptive Statistics

The study builds on the combination of several data sources to construct a comprehensive set of covariates and to control directly for important factors influencing house prices. First, 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 includes all sale listings on the website for houses for residential use. On a monthly level, it covers the period 2007 to 2021. The analysis focuses on the period June 2013 to

[6]The period $t-4$ consists of an additional month (compared to $t-1$ to $t-3$) because of the odd number of total months in the control period.

June 2021 such that data spans equally four years before and after the RNPA has been passed.

The data set has several advantages: First, it is highly disaggregated at the unit level. Hence, the exact geographical location can be used to determine the proximity between the houses and the railroad tracks. Second, the data contains an extensive amount of housing units (around 1.1 million observations are included in the estimation sample). It allows robustness checks and heterogeneity analysis based on subgroups without concerns about sample size. The data set further offers a rich list of house-specific characteristics, that are included in X_{ij} such as living space, number of rooms, number of bathrooms, heating type, and the building's age and condition.[7]. Note that the house price listed in the data represents the asking price based on advertisements. The transaction price might differ from the information used here, but this actual price is unobserved[8].

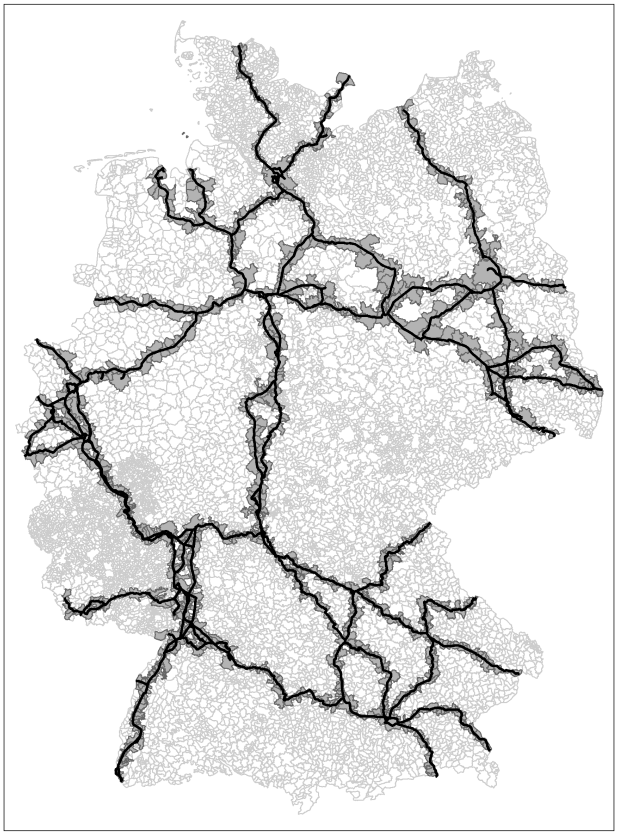
There are six freight corridors for railroad-related transport of goods in Germany[9], which aim to connect all major (industrial) centers in Europe. I rely on data given by the map service of the European Commission (2021) which offers the route of each corridor in detail. The tracks are geographically referenced using Geographic Information System (GIS) tools to make them usable for the statistical analysis. Figure 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.

[7]I restrict the sample by dropping houses with unrealistic values which do not represent the typical homes. Values below the 1st and above the 99th percentiles are excluded. For example, homes sold above 1.9 million Euros or have more living space than 480 square meters are dropped.

[8]For more detailed descriptions of the data and the variables included, see Schaffner (2020).

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

Figure 3: Freight train corridors & Covered municipalities



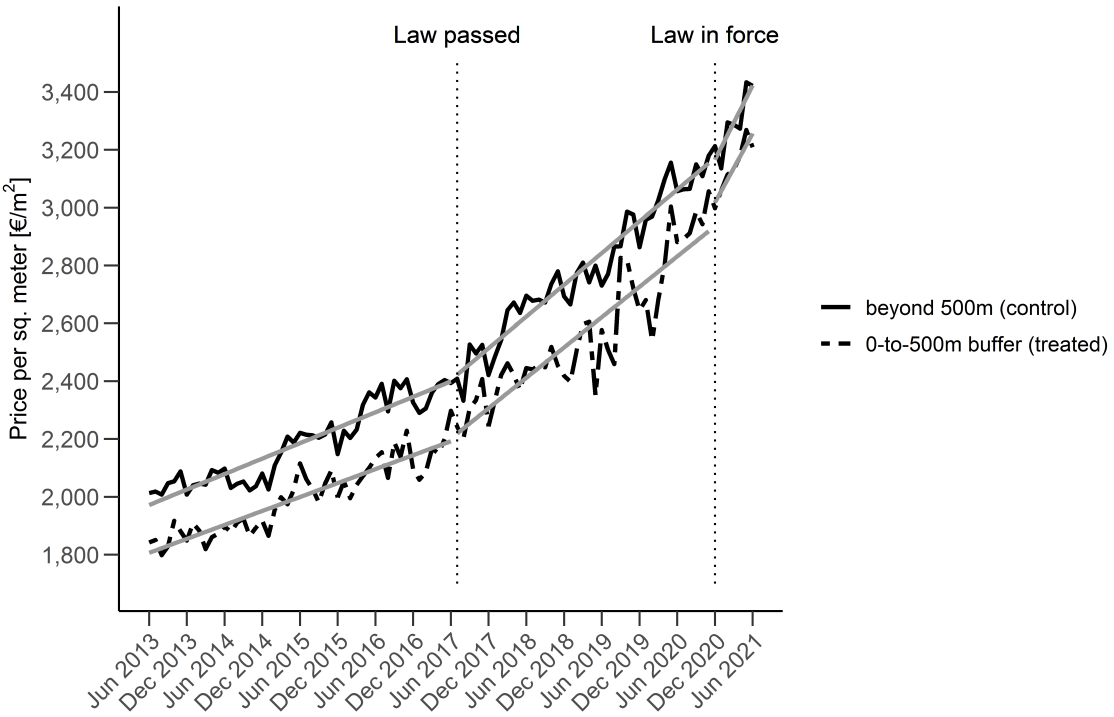
Notes: The figure shows the course of the covered railroad tracks of freight train corridors in Germany (in black) and it also highlights the municipalities crossed by these tracks (in dark grey) which form the treatment and control groups.
Source: Author's graph. The railroad track information is provided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

Based on the housing data and the railroad corridors, I calculate Euclidean distances (i.e., straight-line distances) between the houses and the tracks. In the baseline setting, this buffer is given by the dummy variable *Buffer500*, which is equal to one for those homes that are not further away than 500m from the tracks. Consequently, observations beyond this threshold represent the control group, while those below this threshold belong to the treatment group. To keep both groups geographically close to each other, the maximum distance to the tracks is restricted by the municipality border as shown in Figure 3. The dark grey areas highlight the included municipalites and the restriction of distance. The distance buffer is augmented in the extended version of the model (see Section 4.3). Instead of using one distance, the treated observations are defined by different distance indicators: 50m, 100m, 250m, 500m, 750m, 1000m.

An important assumption for the identification strategy is that the treatment and control group follow the same trend. Figure 4 provides visual evidence for this by showing

the evolution of house prices (as price per square meter) for the baseline setting over time, i.e., homes within 500m from the tracks (dashed line) and those beyond this mark (solid line). Both groups indeed follow the same trend (indicated by grey solid lines). Especially prior to the adoption period (July 2017), housing prices in both groups evolve similarly, supporting the common trend assumption. However, houses closer to tracks (within 500m) perform worse in terms of price over the entire observation period, emphasizing the disamenities these neighborhoods are confronted with.

Figure 4: House prices over time



Notes: House prices (as price per square meter) for the treated group (distance to tracks 0 to 500m) are given by the dashed line, and the solid line represents the control group (distance larger than 500m). The implementation process of the RNPA is denoted by the vertical lines (July 2017 when the law was passed, December 2020 for the law being in force). 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).

As location impacts the prices of homes severely (see, for example, Kiel and Zabel, 2008), I include the straight-line (Euclidean) distances to the nearest (large, medium, or small) regional centers as additional control variables. The data originates from the Federal Office for Building and Planning (BBSR) (2020a). The latest available information for 2017 is used. Based on an accessibility model, the BBSR calculates distances between municipalities and defines centers of importance. These centers serve as a provider of cultural, medical, and general lifestyle services and are significant employment locations.

The BBSR distinguishes between small, medium, and large centers, which differ in their supplied services.[10] In total, the BBSR lists 152 large, 956 medium, and 2,488 small regional centers. Regional centers are incorporated to capture the effects of commuting and the interdependency between regions and municipalities. These distances offer a direct tool to account for location effects.

Since trains are not the sole noise source to impact house prices, I also 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. Major airports[11], which register at least 50,000 starts and landings per year, are included for the distance to airports. I further add airports in metropolitan areas[12] with a population of at least 100,000 citizens, which are not already defined as major airports (UBA, 2019b). 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 the house 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 are reported to have a traffic volume of at least 3 million cars per year.

Living close to railroad tracks does not only imply that housing units are exposed to additional noise by railroads, but the residents may also have better access to them and other traffic modes. Therefore, the Euclidean distances between homes and train stations and also between houses and highway ramps are controlled for. The train stations are provided by DB Station and Service AG (2020), which lists the geographical locations of all public train stations in Germany. As Voith (1993) already pointed out, access to highways is critical when estimating house prices. Thus, highway ramps are collected by Open Street Map data using the tag highway:junction. Both accessibility variables cover entry points to the traffic infrastructure network. The impact of these accessibility variables on house prices could be positive or negative. Debrezion et al. (2011), for example, state a negative

[10] Large regional centers, for example, have a comprehensive health system with general doctors as well as 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 and hence, they are an important factor in the regional infrastructure, particularly in more remote areas.

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

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

effect of the distance to train stations on house prices. For highways, Allen et al. (2015) find that greater distances to the next highway ramp are associated with price decreases. Overall, accessibility is valued positively, and noise and traffic intensity are evaluated negatively (Levkovich et al., 2016). Controlling for these accessibility factors is important as they represent another potential noise source independent of the effect's direction.

Table 1 illustrates all variables and their respective description.

Table 1: Variable descriptions

Variable	Description
A. Object characteristics	
Log price	Logarithm of the asking price for housing objects
Price	Asking price for housing objects (in Euro)
Number of rooms	Number of rooms
Age	Age of the building
Number of floors	Number of floors
Endowment	Classification of the endowment of the object
Number of bathrooms	Number of bathrooms
Plot area	Size of the property area (in m^2)
Heating	Classification of the heating system
Under construction	Indicator for the object 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 object
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: Endowment ranges from simple to deluxe, allowing for four categories in total. Heating describes the source of power and includes types like electric heating, 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.
Source: Author's table.

Table 2 offers summary statistics for the included variables. It is divided into three periods: before the RNPA was implemented (control period, June 2013 to June 2017), when it was passed and under adoption (July 2017 to November 2020), and when the act was fully in place and non-compliance could be fined (December 2020 to June 2021). The summary statistics further differentiate houses within 500m to the tracks and for those further away for each period separately.

Table 2 shows that houses within 500m from the tracks sell, on average, for a lower price at any given time. Comparing differences in mean prices without conditioning

on characteristics already indicates a catching up of close houses after the RNPA was introduced. Houses within 500m to the tracks sold, on average, for approximately 34,000 Euros less than their counterparts in the control group before the RNPA was enacted (prior to July 2017). This deviation reduces to ca. 30,000 Euros during the adoption period and to 21,000 Euros after the RNPA was fully in force. Even though the noise-exposed houses still sell for less than the unexposed ones, the explorative comparison shows a gain of approximately 13,000 Euros in selling prices (or around 2.6% of the transaction price of the treated) when the noise-reducing law was completely enrolled. Similarly, when considering the unconditional difference-in-difference (see columns (7) and (9) of Table 2), the treated houses within 500m to the tracks gained in 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 being fully enrolled.

Table 2 also shows some differences in housing unit characteristics between the treatment and control group. For example, treated houses have a higher average age and a smaller plot area. As expected, homes within 500m of the tracks are also closer to the next train station. Therefore, these homes have an advantage in accessing railroad services, which might increase their attractiveness compared to other homes, reassuring the inclusion of the distance to train stations as a covariate.

Table 2: Summary statistics

	Before RNPA (< July 2017)		RNPA passed (≥ July 2017)		RNPA in force (≥ December 2020)		uncond. DiD RNPA passed		uncond. DiD RNPA in force	
	Dist. to tracks ≤ 500m	Dist. to tracks > 500m	Dist. to tracks ≤ 500m	Dist. to tracks > 500m	Dist. to tracks ≤ 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. Object characteristics										
Log 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. Other 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: Mean values are shown for houses within 500m to railroad tracks (treatment group) and houses beyond this threshold (control group) for the periods before the RNPA was implemented (June 2013 to July 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.

Regarding other data sources in the heterogeneity analysis (see Section 4.3), I study the effectiveness of the RNPA for various degrees of urbanization. I use settlement density to define neighborhoods that are more (less) densely populated. The data is provided by the BBSR (2020b) for 2017 and describes the number of people per square kilometer of residential and traffic areas. It takes on values between 0 and $6,263$ people per square kilometer. The settlement density is then divided based on the quartiles to form subsets leading to the categorization of highly sparse, sparse, dense, and highly dense municipalities.

4 Results

4.1 Main Results

Table 3 column (1) shows the coefficients of interest and the basic noise effect (γ) from estimating Equation (1). Both interaction terms are positive and highly significant. The interaction between the variables *LawPassed* and the treatment ring *Buffer500* shows that houses within 500m to tracks gained on average 0.5% in price compared to houses further away. The effect is even larger after the law was fully in place, i.e., the adoption effect of the first period is much smaller than the actual treatment effect of the RNPA. This seems reasonable as modernization was still an ongoing process during the adoption period. Noise levels might be marginally lower than before the implementation of the RNPA, depending on the number of already upgraded freight trains at that time. Both interactions taken together, the gains in value offset the general negative noise effect of 2%.

4.2 Robustness checks

Table 3 (Column 2 to 5) displays 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 group more similar[13] reduces the sample by roughly $300,000$ units compared to the baseline setting (see column (1) of Table 3). However, the results concerning the impact of the RNPA on house prices do not differ significantly from the baseline results.

[13] in terms of summary statistics

Table 3: Baseline results and robustness checks I

Dependent Variable:			log(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	Yes	Yes	Yes	Yes	Yes
State time trend	No	No	No	No	No
Sample restricted	No	Yes	Yes	Yes	Yes
Fixed-effects					
Month FE	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	No
Zip-code FE	No	No	No	No	Yes
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: Results for the baseline specification and the first set of robustness checks. *Buffer500* indicates houses within 500m of the tracks. *LawPassed* is equal to one for periods between July 2017 and November 2020 and *LawInForce* represents the periods December 2020 to June 2021. 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 in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

Column (3) shows the results without the 15 largest cities with at least 500,000 citizens.[14] 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 similar observation can be made when the exclusion of specific regions is taken one step further. When all cities with more than 100,000 residents are removed, the number of observations drops by around 400,000 (see column (4) Table 3). The estimated coefficients change to 0.8% for the adoption period and 2.1% for the period after the RNPA was ultimately implemented.

By eliminating these metropolitan areas, I aim to exclude potential confounding factors. Large cities can be assumed to have an overall higher noise level due to their size, a more complex traffic infrastructure, and higher building densities. So, the RNPA would

[14]These cities are: Berlin, Hamburg, Munich, Cologne, Frankfurt am Main, Stuttgart, Dusseldorf, Leipzig, Dortmund, Essen, Bremen, Dresden, Hannover, Nuremberg, and Duisburg. They all have an approximate size of 500,000 citizens (except Duisburg, which is slightly below) (Federal Office of Statistics, 2021b).

have a diminished impact as changes in the noise level of one particular source (here, railroad noise) would be harder to identify. However, cities also are focal points of economic and social activities, making them attractive for living and working. Table 3 hints at larger effects when metropolitan areas are removed (except in column (4) for the actual treatment period). This is in line with the expectation that improvements are more recognizable in rather remote areas. Despite the changes in effect size, removing agglomeration areas does not change neither direction nor significance of the results. Large cities do not seem to drive the overall results.

Column (5) of Table 3 displays the results when excluding homes between 500m and $1,000$m from the estimation. The intention is to separate the control and treatment group clearly from each other by introducing the neutral zone. 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 4 shows the results for the second set of robustness checks. 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). 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 group 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 both the treatment and control group.

Table 4: Robustness checks II: Zip-code FE, time trend, pre-trends, and placebo regression

Dependent Variable:			log(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	Yes	Yes	Yes	Yes	Yes
State time trend	No	No	Yes	No	No
Sample restricted	No	No	No	No	Yes
Fixed-effects					
Month FE	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	No	Yes	Yes	Yes
Zip-code FE	No	Yes	No	No	No
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: Results for the second set of robustness checks. *Buffer500* indicates houses within 500m to tracks. *LawPassed* is equal to one for periods between July 2017 and November 2020 and *LawInForce* represents the periods December 2020 to June 2021. Column (1) restates the baseline findings. 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 for limiting the sample to the control period and assuming the treatment to start in July 2015 (placebo test). Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

For the last robustness check, the observation period is restricted to prior July 2017, and the treatment is assumed to start with July 2015. The variable *Placebo* is equal to one for the months between July 2015 and June 2017. Therefore, half of the period is under treatment. As expected, the treatment effect turns out to be insignificant.

4.3 Heterogeneity Analysis

4.3.1 Model extension

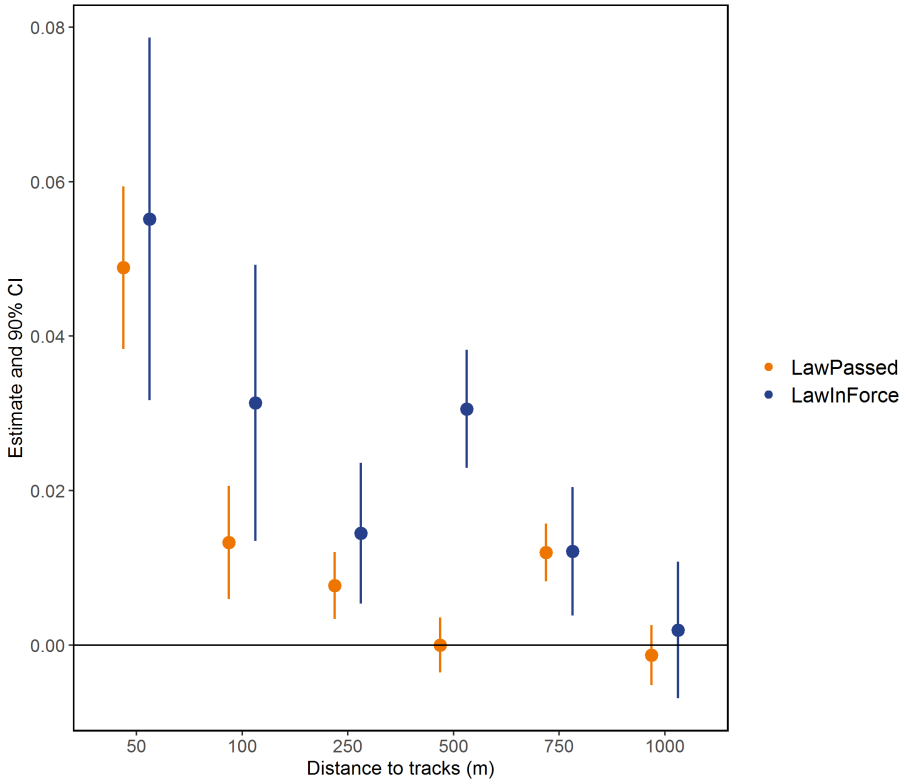
For the first heterogeneity test, I investigate the effect of noise reduction under different treatment intensities, i.e., different distances to the railroad tracks. The baseline model used a distance buffer of 500m. In this setting, six buffers are defined, ranging from 50m to 1000m. Each buffer indicates whether the offered house lies within the respective distance. The control group in this setting is represented by houses beyond 1000m and up to the municipality border.

Generally, closer houses to the tracks are exposed to higher noise levels caused by passing freight trains. The expectation is that the larger the distance between the tracks and the house is, the smaller the impact of the law-induced noise reduction. The results (Figure 5) confirm the aforementioned expectation as the shortest distance (50m) also shows the largest coefficients (4.9% to 5.5%). The adjacent buffer of 100m displays the second highest effects. The coefficients are larger than the baseline results. Overall, the effect magnitude decreases with distance, as expected. However, the results for a distance at 500m disrupt the pattern of decreasing effect sizes with distances. While the effect for the actual treatment period is of similar magnitude as at 100m, the effect for the adoption period is insignificant.

Interestingly, there is no effect for the furthest distance (1000m).[15] This hints at a point up to which the RNPA affects house prices, which is also reasonable as changes in noise levels are mitigated by distance.

[15]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.

Figure 5: Heterogeneity analysis: Model extension



Notes: Coefficients (dots) and 90% confidence interval (vertical lines) for extension of the model by defining six treatment buffers in the range from 50m to 1000m (instead of only 500m 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.

4.3.2 Settlement density

I study the impact of the RNPA under various degrees of urbanization using information on settlement density.[16]

Table 5: Heterogeneity Analysis: Settlement density

Dependent Variable:	log(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	Yes	Yes	Yes	Yes	Yes
State time trend	No	No	No	No	No
Sample restricted	No	No	No	No	No
Fixed-effects					
Month FE	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes
Zip-code FE	No	No	No	No	No
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: Regression output for subsamples of settlement densities. *Buffer500* indicates houses within 500m to tracks. *LawPassed* is equal to one for periods between July 2017 and November 2020 and *LawInForce* represents the periods December 2020 to June 2021. Column (1) restates the baseline results. Column (2) represents highly sparse, column (3) sparse, column (4) dense and column (5) highly dense municipalities. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%. *Source*: Author's table.

Table 5 shows that highly sparse municipalities show mixed results. While the adoption period effect is insignificant, the effect of the RNPA being fully adopted increases house prices, on average, by 1.8%. The coefficients for the sparse type are both significant and have similar sizes to previous results. Densely populated areas show the strongest impact of the RNPA, which is much larger than the baseline setting. The adoption effect is 2.4% and the following period amounts to even 4.2%. Interestingly, the estimates for the highly-dense types do not show any significance. This might be explained by the higher intensity of noise sources. These places accumulate a higher share of business activity,

[16]The variable is divided into groups based on the quartiles of the settlement density and thus, ranging from highly sparse to highly dense regions.

traffic volume and commuting, and population density resulting in less quiet places and overall higher environmental noise levels. Changes in noise of one source (here freight train transport) might be less recognized.

4.3.3 Other noise sources

This section studies the impact of the RNPA on neighborhoods under a particular burden of noise due to the proximity to other noise sources. The analysis originates from the richness of the data. The distances between the housing unit and the noise sources build the foundation to define regions affected by general high levels of environmental noise and disamenities coming from these locations (see Section 3.2 for the description of the single sources). I apply a data-driven approach and use the first and the second quartiles of these distances for the group definitions (see Table 6).

Table 6: Distances to other noise sources (in km)

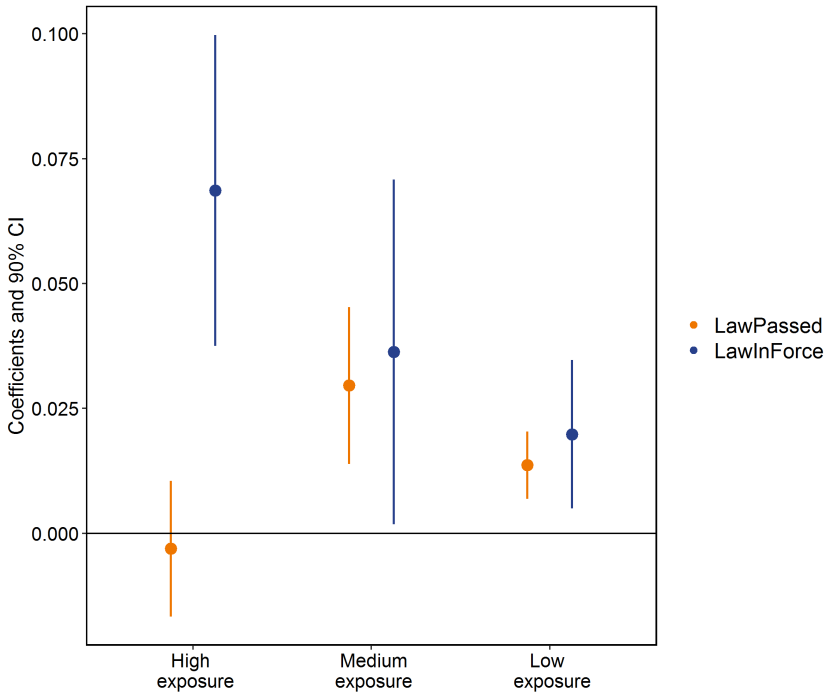
Source	1st quartile	2nd quartile
Airport	8.8	20.4
Ind. plants	3.2	9.0
Main streets	0.2	0.6

Notes: The table displays the distances to other noise sources (airports, industrial plants, and main streets) in km for the first and second quartiles. The noise source information is given by Federal Environmental Agency (UBA) (2019a, 2019b, 2019c, 2019d).
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 places with overall high 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 the second quartile in terms of distance. Finally, the low-exposure neighborhoods are further away than the second quartile, and therefore, I assume that those are also the quietest places concerning the considered noise sources. The baseline regression is then repeated for each subset. Figure 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 6: Heterogeneity Analysis: Highly exposed locations



Notes: Point estimates (dots) and 90% confidence intervals (vertical lines) based on the combination of all three major noise sources. 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.

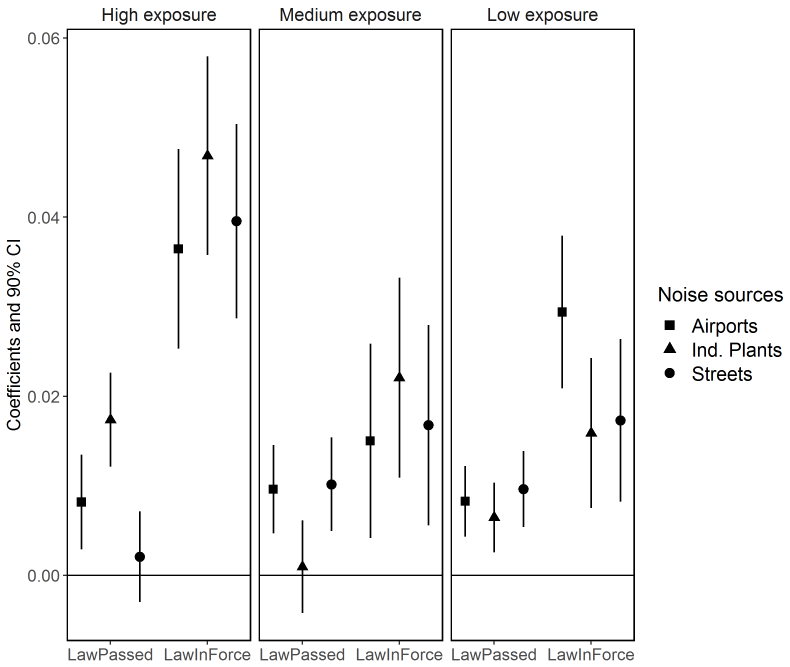
The results reveal that the high-exposure group gained the most from the implementation of the RNPA, at least for the actual treatment period (after December 2020). The point estimates amount to 6.9%, which is substantially larger than any previous effects. The effect for the adoption period is insignificant, 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 one 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. These results, that those having to deal with generally higher environmental noise levels gain the most from a reduction in noise in one sector, are surprising as I would expect that places with lower overall noises gain more as the source of disturbance vanishes.

Effects by distance and source

The second heterogeneity analysis concerning noise sources takes the first exercise one

step further by analyzing the single effects of each noise source. I use the three-group definition of the previous setting (high, medium, and low exposure) again but treat each noise source separately.

Figure 7: Effects by distance and source



Notes: Point estimates (symbols) and 90% confidence intervals (vertical lines) for high, medium, and low exposure locations by the respective noise source. 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.

Analyzing these noise source-specific patterns and using the three exposure groups reveals similar patterns as before. The adoption period demonstrates a smaller impact than 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., those locations that are 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 that live under the highest noise levels near airports, industrial plants, and 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 (see Section 4.3.1). The medium-exposure and low-exposure regions do not vastly differ in their effect sizes.

5 Conclusion

As noise puts people's health at risk and represents a general disturbance, this study evaluates the reduction of railroad-related noise using a hedonic price function setting. Exploiting variation in noise levels caused by the RNPA, which was passed in 2017 and banned loud freight trains, I focus on house sales close to railroad tracks to determine price changes after the law was implemented.

The baseline results suggest an increase of house prices within 500m 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 under different subsets elaborating on heterogeneous treatment effects. Houses in the absolute vicinity of the railroad tracks show the strongest responses. This is an expected result, as these homes have the highest exposure levels and should thus gain the most from noise reductions. The study of the settlement density as the degree of urbanization led to mixed results. Studying the impact of the RNPA in generally noisy places shows that those with overall high noise levels also gain the most from the adoption of the RNPA.

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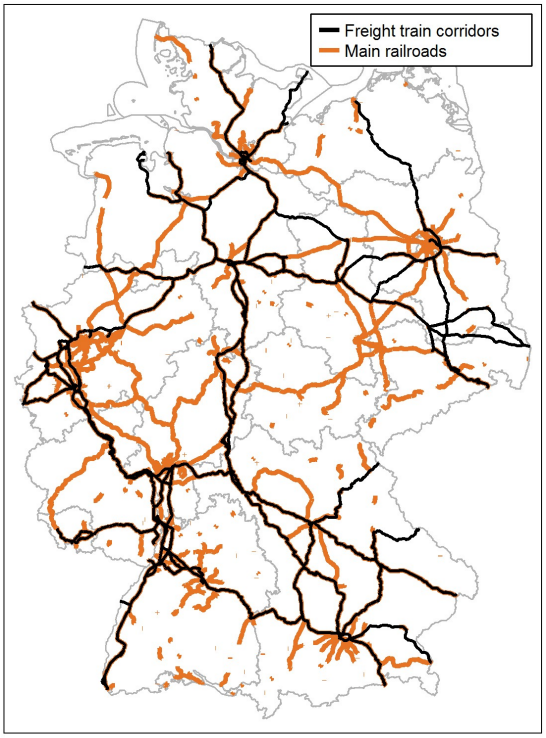
A Online appendix

A.1 Additional robustness checks

Freight train corridors are not the only railroad network in Germany. This robustness check avoids freight train corridors but uses all main railroads. The data is provided by UBA (2019e) for 2017 and consists of railroads that register at least 30,000 trains per year. These tracks are displayed in Figure A1 (orange lines). The previously used network of freight train corridors is plotted as reference (black lines) as well. 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.

Figure A1: 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).

The methodology stays unchanged to test the impact of the RNPA using this alternative set of railroads, i.e., a buffer of 500m is constructed around the main tracks, which is then linked to the house offers. I expect the estimated coefficient to be smaller as 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.

Table A1 shows the results when the freight train corridors are replaced by all main railroads. The adoption effect increases to 1.0% compared to 0.5% in the baseline setting (see Table 3). The actual effect of the RNPA adoption is diminished to 2% as expected. When including other railroad tracks which are also used extensively for passenger transport, the positive impact of the RNPA is indeed diluted at least when the RNPA is fully enrolled. This underlines the effectiveness of the RNPA regarding freight train noise.

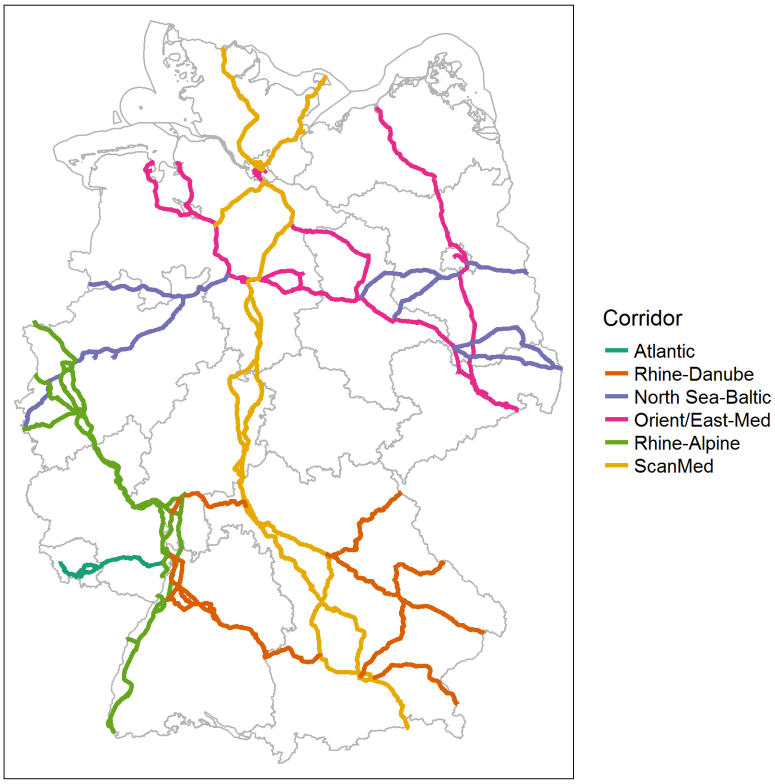
Table A1: Additional robustness checks: Alternative railroads

Dependent Variable:	log(price)
LawPassed × Buffer500	0.010***
	(0.001)
LawInForce × Buffer500	0.020***
	(0.003)
Full set of controls	Yes
State time trend	No
Sample restricted	No
Fixed-effects	
Month FE	Yes
Grid FE	Yes
Zip-code FE	No
Fit statistics	
Observations	1,825,706
R^2	0.81842
Within R^2	0.50141

Notes: Results for replacing the freight train corridors by all main railroads. *Buffer500* indicates houses within 500m to tracks. *LawPassed* is equal to one for periods between July 2017 and November 2020 and *LawInForce* represents the periods December 2020 to June 2021. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

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 A2. For the estimation, each corridor is dropped from the sample separately. The output can be found in Table A2.

Figure A2: 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).

The results in Table A2 suggest a similar effect range across the corridors but with partially more pronounced results, especially after December 2020 (captured by *LawInForce*). The adoption period effect turns out to be insignificant when the North Rhine-Alpine corridor (column 4) and the Rhine-Danube corridor (column 5) are excluded. After the RNPA has been fully adopted, the effect stays highly significant in all scenarios. The results for the leave-one-out estimation are quite similar to the baseline setting.

Table A2: Additional robustness checks: Leave-one-out estimation corridors

Dependent Variable:	log(price)					
Exclusion of	ScanMed	Orient	North-Sea	Alpine	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	Yes	Yes	Yes	Yes	Yes	Yes
State time trend	No	No	No	No	No	No
Sample restricted	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Grid FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-code FE	No	No	No	No	No	No
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: 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 500m to tracks. *LawPassed* is equal to one for periods between July 2017 and November 2020 and *LawInForce* represents the periods December 2020 to June 2021. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.

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

Note, I do not use the information in the main specifications as the data does not contain when the noise barrier was installed. So, it might be possible that I assume that there is a noise barrier close by for a certain house when being sold, but this might be wrong. Further, I include regional fixed effects based on a one square kilometer grid. Thus, I would assume that most of the impact of such omitted noise prevention measures is already accounted for in the main specifications. Following this reasoning, I expect is that including the distance to noise barriers does not heavily change the previous findings. The output is displayed in Table A3.

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 A3: Additional robustness checks: Inclusion of noise barriers

Dependent Variable:	log(price)
LawPassed × Buffer500	0.005***
	(0.002)
LawInForce × Buffer500	0.025***
	(0.003)
Full set of controls	Yes
State time trend	No
Sample restricted	No
Fixed-effects	
Month FE	Yes
Grid FE	Yes
Zip-code FE	No
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 500m to tracks. *LawPassed* is equal to one for periods between July 2017 and November 2020 and *LawInForce* represents the periods December 2020 to June 2021. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.
Source: Author's table.