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Housing Prices, Airport Noise and an Unforeseeable Event of Silence

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Philipp Breidenbach

Patrick Thiel

Housing Prices, Airport Noise and an Unforeseeable Event of Silence

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Philipp Breidenbach and Patrick Thiel¹

Housing Prices, Airport Noise and an Unforeseeable Event of Silence

Abstract

To evaluate the causal impact of noise exposure on housing prices, we exploit a sudden and massive reduction in flight traffic that occurred with the onset of the Covid-19 measures in Germany. Comparing locations differently exposed to pre-pandemic noise with a difference-in-difference approach, we detect a 2.3% increase in prices for apartments that experienced a noise reduction. Disentangling temporal dynamics, we find a peak effect in mid-2021 (up to 6%), which does not yet allow a statement on whether effects remain persistently. In contrast to most evaluations showing that the erection of a disamenity affects prices negatively, we show that lifting the burden enables neighborhoods to catch up again immediately. The immediate catch-up contradicts a stickiness of housing prices regarding (temporal) local factors. The temporal pattern shows a clear peak of the effects during the pandemic, which potentially hints at information asymmetries since buyers may not know the non-pandemic noise level during the pandemic.

JEL-Codes: O18, Q53

Keywords: Covid pandemic; aircraft noise; housing prices; hedonic function

April 2023

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1 Introduction

Noise pollution is associated with substantial costs affecting local residents' physical, mental, and social well-being. Literature of the past decade provides evidence in numerous studies on the substantial impact of airports and the linked noise pollution on health (e.g., Boes et al., 2013; Schlenker & Walker, 2016) and well-being (Lawton & Fujiwara, 2016). Those negative outcomes are typically associated with a declining value of living in such exposed areas. Literature suggests that this decline is also reflected in a decrease in housing prices. Those housing values are not only relevant concerning the housing market, but they 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.

In our study, we use the lockdown during the pandemic due to the Coronavirus disease 2019 (Covid-19) starting in March 2020 and the associated massive decrease in traveling and flights at German airports to evaluate the effects of reduced aircraft noise. While most of the existing studies on noise effects focus on the deterioration of the status quo (additional noise), our study investigates an improvement of the situation at hand, namely a reduction of airport noise and its effect on housing prices.

Compared to many other studies in the literature, our approach has three key advantages. First, the global lockdowns during the Covid-19 pandemic could not be predicted. Since lockdowns with travel bans and closed borders were installed immediately after the outbreak as the most prominent non-pharmaceutical measures to slow down the spread of the virus, the pandemic is characterized by a huge decrease in aviation activities at German airports. Hence, we can clearly characterize the decrease in noise as an exogenous event. Thus, announcement effects or other influences of political lobbying, which may form serious concerns on estimated effects in other setups when noise pollution changes, are not present in our study.

Secondly, our setup allows for the analysis of an event, reducing noise in the areas of intense exposure. Studies focusing e.g., on changes in the routing of approaches are not able to derive the estimated effects from those strongly exposed areas since those routes necessarily remain unchanged in the immediate proximity to the runway. Our setup reveals changes over the whole distribution of the noise exposure. With the onset of the pandemic, aviation noise is reduced in former strongly and weakly affected areas. We can exploit the spatial heterogeneity of the noise exposure to get deeper insights into different levels of noise reduction.

Third, the different stages of the pandemic allow us to measure a decrease in noise

exposure with different expectations on future noise levels (with respect to the aviation market’s future). In the first phase of the Covid-19 pandemic, it was expected that air traffic would return to previous levels once the pandemic was (quickly) overcome. Throughout the pandemic, there has been a growing awareness that air traffic will be permanently restrained. This is particularly related to the increased use of virtual meetings (which may limit business flights in the long term) and the continued growth of government efforts to limit CO₂ emissions. In order to hit the ambitious targets for emission reduction policies, a strong reduction of domestic flights (linked to a reduction of flight activities) also seems to be a suitable instrument to meet future emission goals. At present, there is no clear indication of how the German aviation market will develop in the future. While global air traffic is recovering strongly, inner-German flights are still substantially below the pre-pandemic level.

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 (FEA, 2019a). The offer data (including characteristics and prices) are taken from the RWI-GEO-RED data set, which comprises all offers from the German market leader in housing advertisements ImmoScout24 (RWI, 2021a).¹

We focus on apartments for sale.² Using individual offers, we benefit from the information on the exact geographical location given in RWI-GEO-RED that allows us to directly link the housing data to the information of the aviation-noise contour surrounding the airports. These noise contours illustrate the comprehensive exposition to aviation noise of each location surrounding the airport (before the pandemic). Merging the data on noise and housing offers gives a very detailed impression of the noise pollution that affects the individual offers.

Given the detailed information on noise pollution and the time of the offer for each apartment, we exploit a hedonic framework with a difference-in-difference approach (on the location in a noise-exposed area and the time before and after the onset of the pandemic). This setup allows us to identify the causal effects of the treatment on the treated. The treatment group is defined by apartments within the noise contour of an airport affected by severe aviation noise (above 55dB before the pandemic). The control group only comprises those apartments that are also located close to the airport but that are not declared to be affected by noise.

By defining the control group in close proximity, we want to avoid both groups being affected substantially differently by other developments during the pandemic (e.g., local

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

²We also provide results for the datasets "houses for sale", "apartments for rent", and for the combination of apartments and houses for sale in the appendix.

lockdown measures or shocks in specific branches). Additionally, contradicting effects of the decline of flights (and noise), such as job losses at the airport or aligned businesses, should hit both groups equally. This focus on a geographically very restricted sample can help to detect pure noise effects (see Breidenbach et al. (2021) using a similar setup).

Our results hint at effects of the noise reduction on housing prices. The baseline specification suggests a positive effect of 2.3% with stronger effects for 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 with rather low Covid-19 occurrences, where we find the strongest effect of up to 6%. While these periods are marked by low incidences and lax restrictions, the effect may reflect residents' expectations that the aviation sector will not recover quickly to the pre-crisis level (even if the aviation sector is not actually affected by concrete lockdown measures). Thus, the effect might illustrate a change of residents' perceptions that the pollution will remain lower permanently (compared to the pre-Covid-19 period). 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. First, our study approaches the relationship between housing prices and disamenities in a reversed way compared to most other studies. We do not evaluate the onset of a disamenity affecting apartment prices negatively, but we show a positive effect by the alleviation of a disamenity. Yet, academic research did not focus on insights if neighborhoods, previously exposed to a persistent disamenity, are able to catch up again once such a disamenity vanishes. It stands to reason that prior decades of exposure to aircraft noise also have other socio-structural effects. Better-off households may have left neighborhoods (avoiding the disamenity noise), and decreased prices have attracted worse-off households. Therefore, it is by no means clear that the alleviation of the original burden (of aircraft noise) that has now occurred will actually lead to a symmetrical positive price effect (compared to the negative effects from the onsets of disamenities).

Second, the temporal pattern gives further insights into expectations, adoption speed, adoption ability of the housing market, and potential information asymmetries in the housing market. The significant reaction of housing prices can be interpreted differently in this respect. Purchase prices should reflect the long-term value of the property and not be strongly influenced by short-term improvements in noise levels. If we assume that a 6% price premium (during peak periods) is not justified by the actual (lower level of) reduction in noise over the period of about two years, prices have overreacted during the pandemic. Alternative explanations arise from possible information asymmetries.

In particular, out-of-town buyers who never experienced local noise exposure before the pandemic pay higher prices due to missing knowledge on future noise exposure. This finding may justify mandatory disclosure of noise exposure during the housing transaction process. Another explanation comes from unclear expectations about the aviation market development during and after the pandemic. While air travel increased significantly in 2022 (but is still below pre-crisis levels in Germany), there are also projections that air travel will decline in the long term due to increasing virtual meetings and more climate-conscious flying behavior.

The paper is structured as follows: Section 2 summarizes related studies and provides motivational background information. Section 3 describes the applied empirical strategy and the used data sources. Section 4 lists the results for baseline setting, the heterogeneity analysis, and the robustness tests. Section 5 concludes.

2 Background

From a theoretical point of view, airports can be ambiguous in their effects on the local community. On the one hand, they are an important employer of the region, either directly (e.g., airport personnel or pilots) or indirectly through numerous suppliers (e.g., logistics and construction companies offer their services to or rely on close airports). Airports also play a central role in medium to long-distance travel. On the other hand, they are major pollutants regarding air and noise pollution. Therefore, airports are a burden to those living close by.

The ambiguous effects of airports are also reflected in the existing empirical evidence. In his 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 of the announced expansion of the Greensboro airport in North Carolina on housing prices. In contrast to these negative effects, Brueckner (2003) finds a positive effect of airports on employment, and the studies by Tomkins et al. (1998) and McMillen (2004) point towards a positive effect on house prices due to the proximity to airports. This underpins the possible 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., Ahlfeldt and Maennig (2010), Cohen and Coughlin (2008, 2009), Espey and Lopez (2000), and Lipscomb (2003)). 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 instead of apartments to evaluate airport noise.

One exception is the study by Boes and Nüesch (2011), which uses a change in flight regulations at the airport in Zurich (Switzerland) to show that an increase in air traffic-related noise leads to a decline in apartment rents by 0.5% per decibel (dB) noise increase. Baranzini and Ramirez (2005) find a similar effect (1% per dB increase) for the airport in Geneva (Switzerland). In the German context, Winke (2017) finds that the expansion of the Frankfurt airport resulted in a decrease of 1.7% per dB in apartment prices. Hence, the results from the rental apartments seem to be smaller than for the sales market. This is reasonable as different expectations led to buying or renting a home. As renters are expected to live for a shorter period at one location, they would benefit less from noise reductions. On the other hand, buyers are supposed to stay for years or decades in the same place, and they may not only price their benefit but also the increase of future purchase prices when eventually reselling the apartment. Therefore, they appreciate an improvement in environmental noise more. Ahlfeldt and Maennig (2015) highlight this argument by evaluating the perception of homeowners and renters regarding the proposal to build the new airport Berlin-Brandenburg and to close the old airport Berlin-Tegel.

Since airports are large infrastructure projects, their location does not change suddenly, and even expansions and decommissions are known publicly. They are planned and built over an extensive period, and their location is known long before completion. This open knowledge introduces the challenges of announcement effects since people (and thus housing markets) will start to react once opening plans are published. This creates substantial challenges to avoiding anticipation effects in the setting of such aircraft noise analyses.

As our setup exploits the exogenous variation in airport-related noise due to Covid-19, we avoid most of these common problems in the literature. We are able to analyze the effect of airport noise on apartment prices without being concerned about announcement effects and simultaneity (of positive and negative effects). The Covid-19 crisis was not anticipated by airport operators or residents close by. Additionally, the applied data set providing exact geographical locations of apartments allows us to sharply define control and treatment groups which are generally equally affected by all airport effects other than the noise.

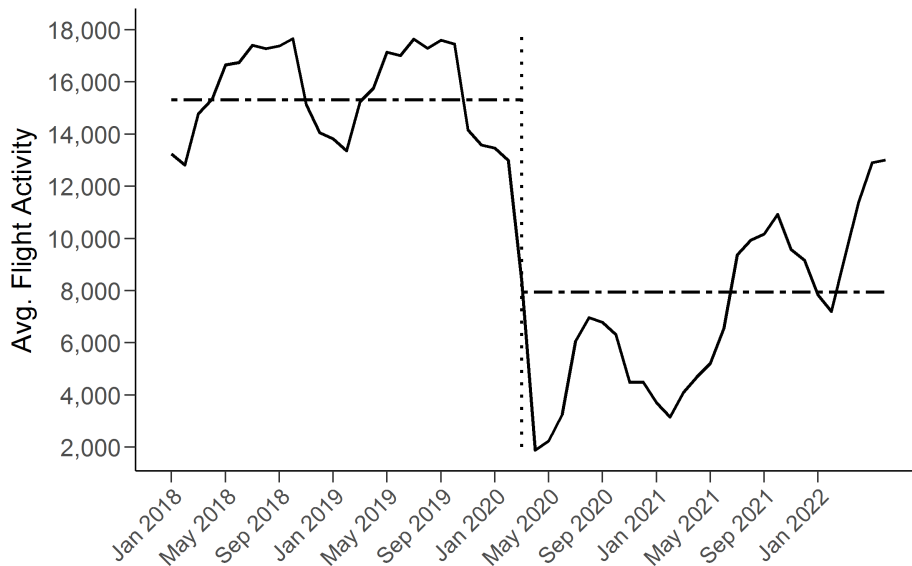
Before the pandemic, there was an increasing trend in air traffic in most countries, including Germany. This pattern changed in March 2020 when travel restrictions were installed in the first lockdown to slow down the spread of the virus. The decrease in airport noise following the pandemic's start is well documented by the number of flight activities at German airports between 2018 and 2022.³ Figure 1 shows the average flight

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

activity for major airports.⁴ While the two observed years before the pandemic show a clear seasonal pattern with peaks of about 17,000 flights per month, the first lockdown pushes this number down to less than 2,000 flights in April 2020. In contrast to the pre-pandemic years, the 2020's peak during vacation time in August only climaxed at about 7,000 activities and still only peaks at about 11,000 flight activities with much less restrictive travel bans in 2021 and to about 13,000 in 2022 without any restrictions. Overall, the period averages (dashed lines) indicate a difference of around 7,000 flights.⁵

To date, the aviation sector did not recover from the dramatic shock caused by the spread of Covid-19. The development of the aviation branch over the long run (and thus the development of flight activities and noise exposure of surrounding inhabitants) is hard to foresee.

Figure 1: Development of average flight activity



Notes: 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.

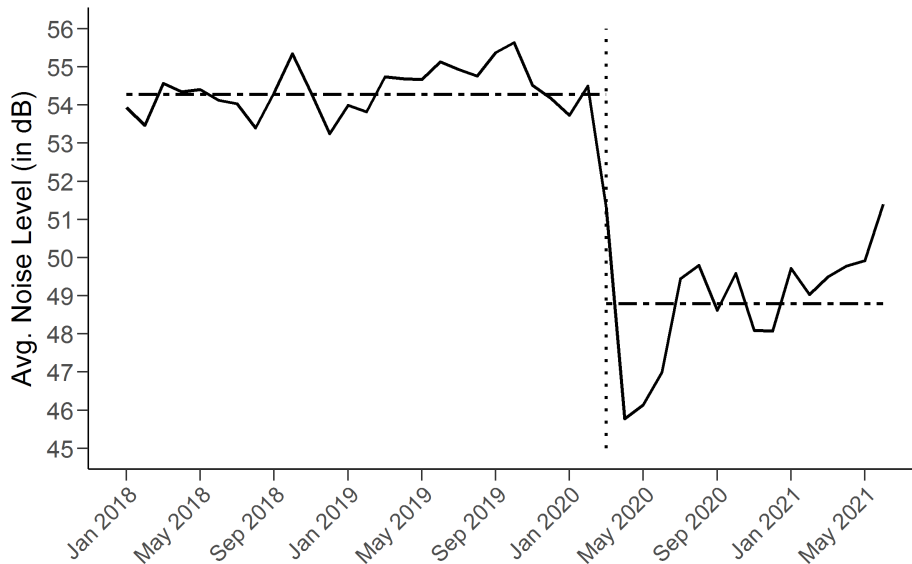
The reduction of flight activity during the pandemic also translates into a decrease in air traffic-related noise. Figure 2 shows the average noise level over time across major

⁴Major airports are classified as airports that register at least 150,000 flight guest units per year. One flight guest unit represents one passenger or 100 kilograms of cargo (FOS, 2022).

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

airports.⁶ The airports themselves provide the data. It is based on measuring stations close to airports and their runways. The average noise level fluctuated between 54dB and 55dB in pre-Covid times with an average level of 54.3dB (dashed line). After the pandemic's start, the noise level dropped to almost 45dB in April 2020. Afterward, the noise level recovered slightly, as did the flight activity. The average of this period under treatment is 48.8dB (dashed line) i.e., still around 5dB below the one of the pre-treatment period. As a benchmark, a reduction in noise of 10dB translates into a decrease in perceived loudness by half (Center for Disease Control and Prevention, 2019) such that a reduction of 5dB is a considerably large 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.

Figure 2: Development of average noise level



Notes: 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 54.3dB) and after the pandemic (around 48.8dB).

Source: Authors' graph. The airports themselves provide the raw data. It relies on measuring stations close to airports and their runways.

⁶In 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 noise measure. It summarizes the noise development over the entire day and adds an extra weight of 5dB to evening times (7 pm to 11 pm) and 10dB to night periods (11 pm to 7 am). Particular noise-sensitive times, therefore, receive special attention.

3 Empirical Setup and Data

3.1 Empirical Strategy

Our main analysis focuses on apartments for sale since 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. Nevertheless, we also show findings for the two housing types (houses for sale and apartments for rent). Since the number of observations for houses in treated regions is quite low and the rents only partly cover the housing value we focus on apartments for sale and show results for apartments for rent and houses for sale in the appendix (see Appendix A.1).

We apply a difference-in-difference approach to a hedonic price function. As originally laid out by Rosen (1974), the hedonic model follows the idea that the apartment price can be described as the combination of the apartment’s characteristics and its surroundings. Our model takes the following form:

$$\begin{aligned} \log(y_{itg}) = & \beta X_{ig} + \gamma \text{NoiseContour}_i + \delta(\text{Pandemic}_t \times \text{NoiseContour}_i) \\ & + \text{Month}_t + \text{Grid}_g + \epsilon_{itg}, \end{aligned} \tag{1}$$

where $\log(y_{itg})$, represents the logarithm of the offering price of apartment i , in year-month t and grid cell g . X summarizes 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.

NoiseContour is the treatment dummy indicating whether an apartment is located within the noise contour of a major airport, i.e., whether the home is exposed to at least an air traffic-related noise level of 55dB (in pre-Covid times). The apartments in the control group are restricted to a maximum distance of five kilometers from the border of the noise contour. Note that the treatment assignment is done on the individual housing unit level. All apartments within a one-kilometer buffer around the noise contour are excluded. This neutral zone drops all homes that might be treated by aircraft-related noise because they are located just at the border of the noise contour. The strategy gives us a clear cut between treated and non-treated apartments.⁷ The variable *Pandemic* is a dummy variable that is equal to one for periods after March 2020 and zero prior to that. We use March 2020 as the start of the pandemic as the federal government restricted public life with the first lockdown in that month to limit the spread of the virus. The interaction term

⁷We relax this setting in one of the robustness checks and incorporate the neutral zone in the sample as part of the control group.

Pandemic x NoiseContour combines the pandemic dummy and the previously described noise indicator such that δ is our main coefficient of interest. It identifies the noise effect on apartment prices for homes within the noise contour compared to the counterfactual scenario without noise reduction and represents the average treatment effect on the treated (ATT).

During the course of the analyses, we further split the interaction term *Pandemic x NoiseContour* in different pre- and post-pandemic time spans. This allows us to analyze the described time patterns during the pandemic and additionally allows us to test for parallel trends of control and treatment group before the onset of the pandemic. Spatial heterogeneities regarding the noise intensities are exploited by splitting the variable *NoiseContour* by the different levels of noise intensities.

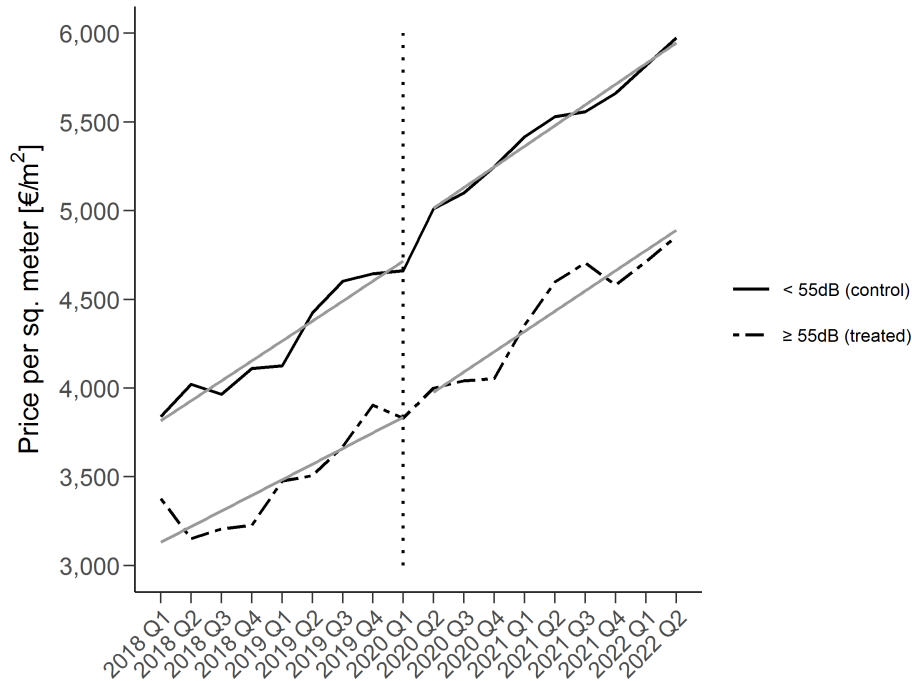
To further complement this small-scale setting, we introduce grid and year-month fixed effects to control for invariant confounders. The regression is performed with robust standard errors. We also run the analysis with various levels of clustered standard errors in Appendix A.2.

As we are estimating a difference-in-difference model, the development of prices before the shock occurs is a central issue for identification. We plot the average price per square meter (in Euro) by quarter in Figure 3. It allows us to draw three observations: First, both the control and treatment groups follow an upward price trend. At the beginning of our observation period, prices ranged between 3,000 and 3,500Euro/m² for treated apartments and just below 4,000Euro/m² for the control group. In the second quarter of 2022, prices have risen to around 5000Euro/m² for the treated and to 6000Euro/m² for the control group. This is an extensive price increase over a relatively short period. The second observation is that the treatment region shows lower price levels than the control group at any given time. The figure suggests that apartments closer to airports that are exposed to higher noise levels can be sold, on average, for less. Lastly, the price curve of the apartments within the noise contour (treated) is more volatile than the control region. This is caused by the lower number of observations in the treatment group, as housing data and average prices fluctuate over time quite strongly. Regardless, both groups follow quite similar trends, which are econometrically tested in the result section.

Note that Figure 3 might hint at pre-Covid effects in prices in the quarters Q4 2019 and Q1 2020, but the figure only shows explorative statistics without controlling, for instance, for apartment characteristics. Our robustness checks suggest that when controlling for the discussed covariates, there are no effects prior to the start of the pandemic dispersing any difference in groups prior to the shock. Further, trend lines hint at an increase in price levels for the control group but not for the treatment group in the first quarter of

2020. This is at odds with our hypothesis of an increase in apartment prices as a result of treatment. Note that this unconditional visual inspection cannot replace comprehensive analyses. Controlling for characteristics accounts for local conditions. Figure A1 hints at a likely change in the regional composition of the control group. After the onset of the pandemic, we see that the share of apartments in the surrounding of Frankfurt increases within the control group. This change in the composition may also affect the mean values. Nevertheless, the outlined empirical model allows controlling for those composition effects by the inclusion of grid fixed effects.

Figure 3: Price development by quarters



Notes: Prices per square meter by quarter for treated apartments (within the noise contour and exposed to at least 55dB of air traffic noise) [dashed line] and control apartments (beyond noise contour and a noise level below 55dB) [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.

3.2 Data

The pandemic and the lockdown measures substantially affected the economy and the society in various areas. Thus, our identification strategy must allege strong arguments, showing that the pandemic did not have assailed our treatment group differently compared to the control group via other channels than aviation noise. We focus on a highly geographically restricted area with the control and treatment group being in close proximity to each other to avoid such potential differences other than noise reduction.

Based on this spatially specific setup, we show that the control and treatment group do not differ substantially in socio-economic characteristics, supporting the argument that the pandemic should not have affected these two groups differently (in other ways than the described noise reduction for the treatment group). To derive solid comparisons between the control and treatment group in key (socio-economic) characteristics, we exploit the RWI-GEO-GRID data set (RWI, 2021b). The RWI-GEO-GRID offers characteristics (like purchasing power and population characteristics) on a one-square-kilometer grid for all of Germany.⁸ The outlined comparisons are based on the last pre-Covid year, 2019. We include the following variables: demographics like household and population density and the share of the working-age population per grid, which is defined for ages between 18 and 65 years, as well as socio-economic factors like the annual household purchasing power (in Euro) and the annual unemployment rate (in percent) per grid. The summarizing statistics are calculated separately for the control and treated regions and are shown in Table 1.

Table 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	967.651	1726.901	683.482	1205.413	6.258 (0.000)
Population density	1815.156	3075.942	1346.984	2370.479	5.453 (0.000)
Working population (%)	62.148	4.401	62.456	5.066	-1.881 (0.060)
Socioeconomic factors					
Puchasing power (EUR)	50685.713	10425.325	50081.007	10774.327	1.697 (0.090)
Unemployment rate (%)	4.657	3.366	4.845	3.524	-1.624 (0.104)

Notes: 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, 2021b).

The demographics show that control and treated regions differ in the number of people and households living in the 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 Covid19. We test for the impact of lower-density neighborhoods (in terms of people and households) in one of the robustness checks (see Section 4.3).

The household purchasing power and the unemployment rate are comparable between both groups (see Table 1). Same accounts for the working-age population. Looking

⁸The data is originally provided by microm GmbH. A detailed description of the data can be found in Breidenbach and Eilers (2018).

at the means and standard deviations does not suggest that the treatment and control groups might be affected differently by Covid-19 (other than in reducing noise).⁹ The observed socio-economic characteristics do not give a clear hint that the groups are affected substantially differently by the pandemic in other aspects than the aviation noise.

Overall, the summary statistics of the grid cells of the treated and control regions illustrate a picture of two quite similar groups regarding some key (economic) characteristics. This strengthens the argument that we compare similar neighborhoods in our empirical setting, giving us no hints (except the different population densities tackled in the robustness tests) that both groups are affected differently by the pandemic (via other channels than noise exposure).

Our empirical strategy requires the combination of two main data sources. First, we employ the RWI-GEO-RED data, which offers listings of apartments for sale made available on ImmoScout24.de (RWI, 2021a). Our observation period is from January 2018 to June 2022. The RWI-GEO-RED covers individual apartment prices on a monthly level, including several apartment characteristics (e.g., size, number of rooms, and indicators, for instance, for having a garden or balcony). Using precise geographical coordinates, we can map each apartment to the noise contour of the nearest airport.

During the data cleaning process, we exclude apartments with characteristic values below and above the 1 and 99 percentiles. The aim is to avoid unrealistic values due to fake listings and typing mistakes on ImmoScout24. We also drop any apartment offers from March 2020 (in the baseline setting), as this is the start of the pandemic. As the apartment data is given monthly, we cannot distinguish if the offers of March 2020 belong to the pre- or post-treatment period. A detailed description of the apartment data can be found in Schaffner (2020).

We link the housing data with our second data source, the noise contour maps of major airports from the Federal Environmental Agency (FEA, 2019a). These maps define areas around airports and their runways to indicate areas of particular noise exposure. The resulting noise intervals typically range from 55dB to above 75dB. The noise maps assume that aircraft noise above 55dB causes a special burden. Merging both data sets allows us to determine the noise level for each apartment on the individual housing unit level.¹⁰

Figure 4 shows such a map for Hamburg Airport. The smaller the distance to the airport and its runways, the higher is the noise level. The left panel shows the noise

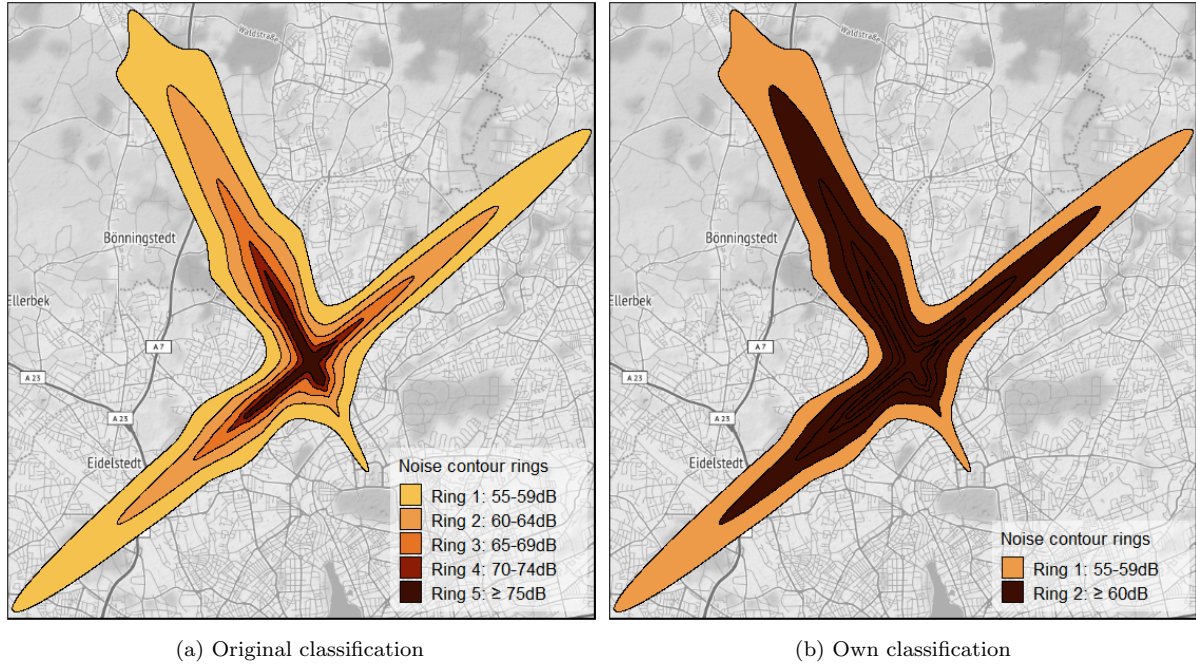
⁹The non-significant differences between the groups are based on the use of a 5% significance level.

¹⁰We also employ the same data source for other housing types (houses for sale and apartment rent) and apply the same empirical strategy. However, the results do not allow for a causal interpretation (see Appendix A.1).

contour rings as given by the original source, with intervals ranging from 55dB to over 75dB. The right panel collapses the five rings into two rings due to the lower number of observations in the inner rings. This setting is used in the later heterogeneity analysis (see Section 4).

Note that the stated noise levels in these maps refer to pre-Covid times. As Figure 2 has shown, the noise level dropped massively after the first lockdown.

Figure 4: Noise contour map of the Hamburg Airport



Notes: Noise contour map of the Hamburg Airport. 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 (FEA, 2019a). The background map is constructed from the open-source Stamen Design.

We restrict our analysis to the main airports in Germany. The Federal Office of Statistics (FOS) defines airports that have at least 150,000 flight guest units per year as major airports.¹¹ This results in 23 main airports in Germany for the year 2021. These airports made up 99 percent of Germany's volume of transporting passengers and goods carried by aviation in 2021 (FOS, 2022). Since the FEA does not generate maps for all of these main airports but only for those that register a minimum of 50,000 in air traffic movements, only eleven maps are available.

Of these eleven airports, two are located in Berlin. We exclude Berlin completely from the analysis for two reasons: First, Berlin had two airports for a long time – Berlin-Tegel

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

and Berlin-Schoenefeld. With the construction of the new airport, Berlin-Brandenburg, which was planned to be completed in 2011, Berlin-Tegel was supposed to shut down. As the construction got delayed, Berlin-Tegel remained open for business leading to a phase of ten years in which the airport operated under uncertainty of continuation. Berlin-Brandenburg was finished in 2020 and started operation in December. Berlin-Tegel was ultimately closed. Further, the new airport was merged with the existing Berlin-Schoenefeld, so the city only had one airport left. Due to this change in the city's infrastructure and the uncertainty involved around the opening of Berlin-Brandenburg and the closing of Berlin-Tegel, Berlin's airports are excluded.

The second reason to exclude Berlin arises from the city's decision to restrict the development of rents. In 2020, the Berlin Senate agreed to counteract the steady increase in the city's rent prices. They established a rent freeze (in German: Mietendeckel) aiming to stabilize the rent levels for the next five years. The Federal Constitutional Court lifted this regulation in 2021. Similar to the airport situation, some uncertainty is involved in the apartment market. Even though Berlin's regulation focused on the rental market, it might be possible that the impermanence carried over to the sales market. Since we are studying the impact of noise reductions on apartment prices, this rent freeze clearly prevents free development in the housing market. Our estimates, therefore, might be compromised if Berlin were included in the sample. Our analysis includes nine major airports, which are depicted in Figure 5. Even though only nine of the originally 23 major airports remain in the study, these airports cover a substantial amount of air traffic. They consolidate 77.6% of passenger transport and 95.6% of the cargo among the main airports in 2019 (own calculation based on FOS, 2022).

Figure 5: Locations of major airports



Notes: Locations of major airports included in the analysis.

Source: Authors' graph. The locations are given by FEA (2021). The spatial information of the states is given by the Federal Agency for Cartography and Geodesy (2019).

We complement our data set by adding additional controls. First, the Euclidean distance to the nearest regional centers is included as a covariate. The definition of these centers is provided by the Federal Office for Building and Planning (BBSR, 2020). We use the latest available data from 2017. Using an accessibility model, the BBSR defines municipalities of regional importance leading to the classification of large, medium, and small centers.¹² Therefore, we aim to directly control for the interdependence between regions by including the distances to these regional centers. Additionally, commuting

¹²The aim is to ensure equal living conditions even for remote locations (Friedrich et al., 2021). These centers provide a wide variety of services to the local community, from shopping opportunities, leisure activities, and transportation infrastructure to health and administrative services. The type of service and degree of specialization depends on the size of the regional center. Large regional centers, for instance, offer education at the highest level, with opportunities to visit universities, specialized libraries, and different kinds of museums. On the other hand, medium centers ensure a broader education lacking this specialization (Einig, 2015). Further, the large and medium centers are particularly important for working and representing business centers (Friedrich et al., 2021). They can also be considered stabilizing factors, especially in remote areas (Milbert & Furkert, 2020).

plays a central role for many households, which in turn impacts housing prices, and by adding these variables to the analysis, we directly control for this relationship.

We include the Euclidean distance to the airport building as a second additional control variable. As outlined in Section 2, airports may have an ambiguous effect on housing prices: As a disamenity due to noise and air pollution or as an economic hub, providing a working place either for people, e.g., directly employed at the airport or for suppliers located close by. They also offer travel opportunities for medium to long-distance travels. Without a covariate capturing this positive effect, our estimates may be biased (see Section 2). FEA (2021) provides the geographical information, which offers a data set with all worldwide registered airports on openflights.org. Additionally to the major airports shown in Figure 5, airports in agglomeration areas are added to the list because they are also eligible for the construction of noise maps by the FEA. This addition accounts for the fact that the closest airport for a specific apartment might not be a major one but rather a city airport.¹³

We further add the Euclidean distance to major railroads, streets, and industrial plants. FEA (2018) provides the data for major railroads, which consists of all railroads that register at least 30,000 in train movements per year. Similarly, we use the same data source to include the distance to major industrial plants in agglomeration areas (FEA, 2019b) and distances to main streets with a traffic volume of at least 3 million cars per year (FEA, 2019c). Adding these additional noise sources allows us to control for their negative noise effect on apartment prices. Therefore, the estimates presented later reflect only the aircraft-related noise effect. Note that all included distances are calculated in kilometers.

Table 2 provides the summary statistics for the apartment characteristics and the discussed additional control variables. It is divided into treated homes, i.e., those within the noise contour and, therefore, exposed to aircraft noise, and control apartments not extensively affected by air traffic-related noise. The table also indicates the summary statistics before and after the first lockdown (March 2020) and offers unconditional difference-in-difference estimates.

Table 2 supports the visual impression from Figure 3 that apartments with aircraft-related noise sell for less, on average. However, the table also shows that the treatment and control group are comparable in key characteristics.

¹³These airports are located in Essen/Mühlheim, Mannheim, Dortmund, Bremen, Mainz-Finthen, and Dresden. Note that these airports are otherwise not part of the analysis. Despite the noise contour maps being available they lack importance as they register less than 50,000 in take-offs and landings per year. Further, only a few apartments are located in close proximity resulting in a low number of observations disqualifying them for the regression analysis. This also prevents additional analysis regarding the difference between main and regional airports.

Table 2: Summary statistics

	Treated		Control		Uncond. DiD	
	Before pandemic	After pandemic	Before pandemic	After pandemic	Estimate	SE
	(1)	(2)	(3)	(4)	(5)	(6)
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
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
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: 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.

4 Results

4.1 Main Results

Table 3 shows our baseline results. Our preferred specification is the column (3), which includes time and regional fixed effects on a 1x1 kilometer grid level. The unexpected but substantial reduction of noise pollution positively affects those apartments exposed to aviation noise. With the onset of the lockdown (causing the reduction of noise), the offer price for those apartments increases by 2.3% in relation to the apartments in the control group which are not exposed to noise (in normal times) but are also closely located to

airports.¹⁴

The columns 1 and 2 of Table 3 reveal the importance of sound control variables in the hedonic regression approach. When we do not control for individual dwelling conditions (column 1) and time-persistent differences in the local neighborhood on the grid level (column 2), the effect cannot be adequately estimated. Performing analysis without dwelling characteristics or with broader airport fix effects (instead of grid fix effects) results in no effect. A finding which is also visually reflected in the previously shown price trend graph (see Figure 3) and given by the unconditional diff-in-diff in Table 2.¹⁵ As the insertion of the local fix effects has high relevance for the estimated coefficient, we test for the robustness of the results with respect to varying local fixed effects, using 250x250 meter, 500x500 meter, 5x5 kilometer grids and zip-code fixed effects presented in Table 6.

Table 3: Baseline results

Dependent Variable:	log(apartment price)		
	(1)	(2)	(3)
Pandemic \times NoiseContour	-0.012 (0.011)	-0.005 (0.006)	0.023*** (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: Baseline results with *Pandemic* indicating periods after March 2020 and *NoiseContour* being equal to one for apartments within the noise contour of major airports. Column (1) shows the unconditional estimation with 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. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.

Source: Authors' table.

¹⁴Note that we directly interpret the estimated coefficient as a percent change as the coefficient is 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).

¹⁵The changes of characteristics between treated and non-treated dwellings before and after the onset of the pandemic, as presented in Table 2, hint at the importance of the controls. The endowment and the condition of treated dwellings got worse after the onset of the pandemic, which does not hold true (in the same manner) for the control group. The same holds for the age of the building. Additionally, the dwellings offered in the treated area after the pandemic are more distant to medium centers, suggesting that more remote locations are offered in the treatment group. This highlights the importance of precise local fixed effects as given by the 1x1 km grid fixed effects.

4.2 Heterogeneity Analysis

The baseline finding suggests a positive average treatment effect on the treated after the pandemic’s start. Next, we investigate how the effect differs under various scenarios.

We exploit the richness of our data in the first heterogeneity test by dividing the noise contour into two rings to test whether noise intensity plays a role. If the storyline from the baseline results that apartment prices respond positively to noise reductions carries on, then apartments with higher noise levels should react stronger to falling noise levels.

The first ring sums up noise levels between 55 and 59dB. The second ring assumes a stronger noise intensity and registers noise levels above 60dB in pre-Corona times. A graphical representation of these rings is displayed in Figure 4 (right panel). This differentiation allows us to identify the treatment effect of the noise reduction for previously weakly and strongly exposed apartments. Table 4 shows the main coefficient of interest.

Table 4: Heterogeneity Effect – Noise Intensities

Dependent Variable:	log(apartment price)
Pandemic \times Ring 2 _{High}	0.043*** (0.011)
Pandemic \times 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: Heterogeneity analysis assuming different noise intensities with Ring 1 indicating areas with a noise level of 55 to 59dB (low noise before the pandemic) and Ring 2 identifying regions of noise levels above 60dB (high noise). *Pandemic* indicates periods after March 2020. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.

Source: Authors’ table.

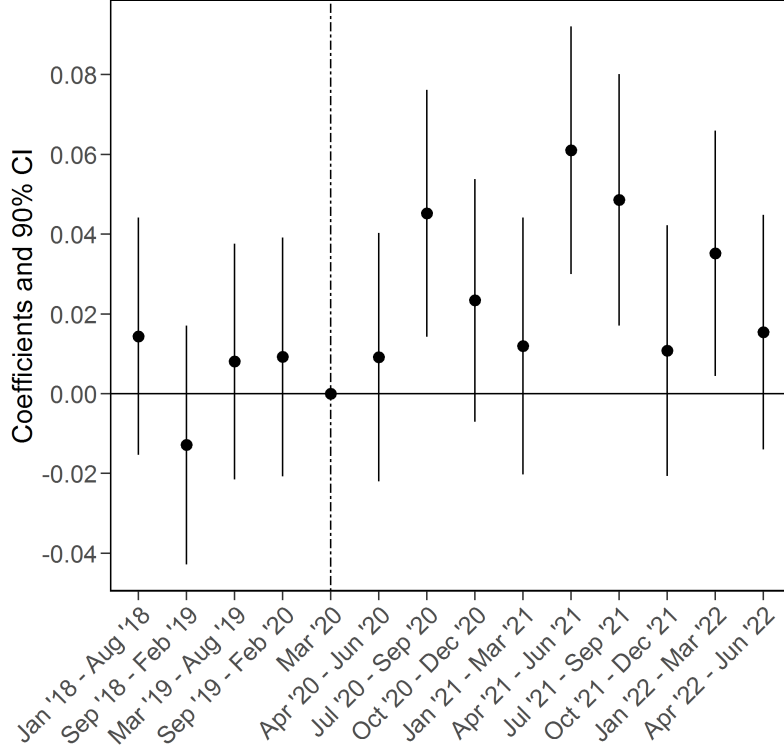
As expected, the effect is substantially larger for those apartments with higher noise exposure (4.3%) in contrast to the effect of 1.8% for the lighter affected apartments. These findings suggest that previously high noise levels are associated with stronger price reactions when experiencing noise reductions.

Next, we study the temporal patterns of the effect over the course of the pandemic. As the reaction in the prices. To analyze the different effects of the pandemic, we split

the post-pandemic period into intervals of three months and the pre-pandemic periods into six-month intervals.¹⁶ The reference period is March 2020. The period indicators are then interacted with a dummy that captures proximity to airports (*NoiseContour*).

Figure 6 reports the results of these interaction terms graphically.

Figure 6: Heterogeneous Effect - 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. These intervals are then interacted with the treatment indicator (*NoiseContour*). Point estimates are indicated by dots. The vertical lines show the 90% confidence intervals.

Source: Authors' graph.

The results in figure Figure 6 hint at a temporal pattern over the course of the pandemic. The first period after the lockdown (April-June 2020) did not cause any effects on apartment prices. This may be caused by the general perception that the measures against Covid-19 are only short-term and will have a foreseeable end. The effect increases during the summer period in 2020 when many national restrictions were lifted, but air traveling still did not recover to the pre-pandemic level. Overall, the effect is the largest in the summer of 2021 with effect sizes between 4.9% and 6.1%. Although the number of

¹⁶The change from six months to three months is because we want to study the temporal (potentially seasonal) pattern in the post-treatment period. In general, a six-month interval is better because it provides more power due to the higher number of observations per bin, but it also absorbs the seasonal pattern due to the aggregation.

flights was recovering at this time (to a lower level than before the pandemic), we observe the strongest effect here. It may be caused by the perception of residents (and people moving into such exposed neighborhoods) that the aviation market will not fully recover.

Finally, Figure 6 shows an effect in January to March 2022 (around 3.5%). Finding these late positive effects, even though the impact of the pandemic on people's mobility is reduced, travel restrictions have been lifted, and flight activity increases may indicate that the housing market reacts to more than the pandemic shock. While the effects in 2020 and 2021 might be attributed to noise reductions, the finding in 2022 might be rather associated with the changing aviation industry.

With regard to the aviation sector, it is unclear how the pandemic is perceived by local residents. On the one hand, most pandemic measures have already been lifted in 2022. The level of aircraft movements at the considered airports, which averaged about 50% of the pre-pandemic level during the pandemic, has risen again to about 90% of the pre-crisis level by mid-2022 (see Figure 1). From this perspective (recovery of the aviation market to its original level), no effects of the pandemic should be expected in the long term.

Hence, the observed price effects (especially the price peaks) during the pandemic seem unexpected at the first glance. They can be explained by either information asymmetries between buyers and sellers or by an overreaction in price formation processes. In particular, information asymmetries may have been present when buyers of real estate are 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, mandatory information about expected noise levels would help buyers because asymmetries can be reduced.

If buyers can correctly assess noise impacts, then in pandemic years they have paid a price premium for temporarily mitigated noise impacts that does not seem justified in the longer term. With aircraft movements returning to roughly pre-pandemic levels, the observed price premiums would reflect amenities which only pay off within the pandemic years.

Alternatively, arguments can be made that noise from aviation will not return to its pre-crisis level. Indications of this development can be derived, for example, from aviation industry stock price trends that reflect the long-term economic expectations of

the industry (see Figure A2 in the appendix).¹⁷ Another indication of this is provided, for example, by the fleet management of Lufthansa (the largest airline at German airports), which so far only plans to re-activate three of the originally operated 14 A380 aircrafts.¹⁸ These planes represent the largest and therefore also one of the noisiest aircraft types. Other airlines, which subsequently increase their operations, may also not directly (or never) start operations with their oldest (and thus noisy) aircraft types. However, even under the assumption of 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 cannot provide a clear indication of whether higher prices tend to be persistent, the peak effects are no longer reached.

4.3 Robustness Tests

We perform numerous robustness tests to check the stability of our findings. First, we conduct a placebo test where we restrict our observation period to prior to March 2020 and move the start of a placebo pandemic to March 2019. Table 5 (column 1) shows no significant effect for the placebo test strengthening the parallel trend assumption.

We also test for unique developments on the municipality level by adding a municipality-specific time trend to the analysis. The effect magnitude decreases compared to the baseline finding. However, it still points in a positive direction indicating that apartments exposed to aircraft noise gain in value after the event of silence (see Table 5 column 2).

The next two robustness checks refer to regional population densities. As Table 1 indicated, the mean density of population and households is lower in the treated area.¹⁹ This difference may cause identification problems since people might increasingly value a lower density right after the onset of the Covid-19 pandemic. Hence, our effect would be driven by the increasing popularity of sparsely populated areas instead of the pandemic-induced noise reduction. We test this hypothesis by using the RWI-GEO-GRID data set (RWI, 2021b) to identify less populated grids. We remove areas with less than 1,443 people and 716 households, which refers to the 10% percentile respectively. Columns 3

¹⁷Development of the stock prices hints at persistent effects. We do so by plotting the time trend for the German stock index, the DAX 40 (as representatives of the whole economy), and air-traffic-related stocks. Both time series are standardized to a value of 100 in the baseline period (January 2018). Unsurprisingly, aviation stocks, which outperformed the general economy before the crisis, faced much stronger losses with the onset of the Covid-19 pandemic. Both stock bundles demonstrate a recovery process after the summer of 2020. The DAX even exceeded its pre-lockdown level in 2021. The aviation sector also experienced some recovery but stabilized at much lower levels. This may hint at rather permanent changes in the industry, at least in the medium run.

¹⁸<https://www.aero.de/news-44365/Lufthansa-nennt-A380-Ziele.html> [Accessed: February 2023].

¹⁹This finding comes as no surprise since airports are more likely to be located at the edge of cities where grids are also less likely to be densely populated.

and 4 of Table 5 disperse the concerns that sparsely populated neighborhoods drive our findings as both tests show similar effects as before.

Table 5: Robustness - Placebo, time trend, and regional densities

Dependent Variable:	log(apartment price)			
	(Placebo)	(Time trend)	(Population density)	(Household density)
	(1)	(2)	(3)	(4)
Placebo pandemic \times NoiseContour	0.001 (0.007)			
Pandemic \times NoiseContour		0.018*** (0.006)	0.027*** (0.005)	0.027*** (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: Robustness tests with column (1) showing the results for the placebo test, 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 in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.

Source: Authors' table.

Our main specification removes 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. All neighborhood characteristics should be very similar to those of the apartments that are treated by noise. To test for the importance of those apartments located within the previously neutral 1km buffer zone, we reverse the previous setting and include the neutral zones here. Column 1 of Table 6 shows that including the neutral zone reduces the previously found effect. This finding suggests that there are spatial spillovers right at the border of the noise contour, speaking for the exclusion of the neutral zone.

We included in all settings so far regional fixed effects on a one-square-kilometer grid. We change this setting and introduce fixed effects on different grid sizes of 250m, 500m, and 5km. Especially the smaller regional fixed effects are much stricter in terms of un-

observed characteristics that cannot be directly controlled for in the model. Table 6 shows that our findings are stable to this change in fixed effects. It also shows that using zip-code fixed effects lowers the effect magnitude (column 5). However, these regional units might be too large to capture the local conditions speaking for including the smaller one-square-kilometer grids.

Table 6: Robustness - Neutral zone and regional fixed effects

Dependent Variables:	log(apartment price)				
	(Incl. NZ)	(250m FE)	(500m FE)	(5km FE)	(Zip-code FE)
	(1)	(2)	(3)	(4)	(5)
Pandemic \times NoiseContour	0.018*** (0.005)	0.018*** (0.005)	0.022*** (0.005)	0.019*** (0.005)	0.011** (0.005)
Full set of controls	✓	✓	✓	✓	✓
Time trend					
Fixed-effects					
Months	✓	✓	✓	✓	✓
1km grids	✓				
250m grids		✓			
500m grids			✓		
5km 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

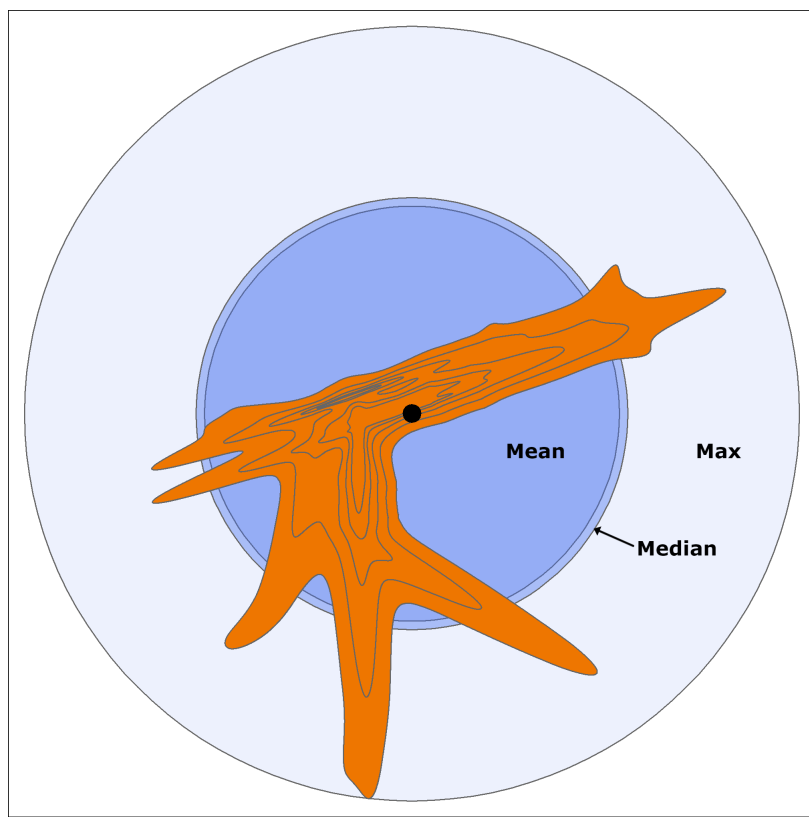
Notes: Robustness tests with column (1) showing the results for including the neutral zone, and column (2) to (4) varying the regional (grid) fixed effects from 250m to 5km. *Pandemic* indicates periods after March 2020 and *NoiseContour* is equal to one for apartments within the noise contour of major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

Finally, we also study the impact of altering the control group definition. In the previous settings, we assigned all apartments beyond the noise contour but within 5km to the control group. It is possible to argue that this setup includes control apartments that are quite far away from the airport and, thus, are different in key characteristics. Moreover, apartments in the heading of the runway may still suffer from noise since approaching planes directly pass by here. They are exposed to noise that might only be slightly below the threshold of observable exposure of 55dB.

In this robustness check, we rely on the airport itself (instead of the contour) and calculate the distance between the airport building and each point of the contour. We then take these distances' mean, median, and maximum 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 stays 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 in the heading of the runway are excluded by definition. Figure 7 shows the definition of these distance rings for the Frankfurt airport. Note that the used distances are airport-specific as they are based on individual contours. We also test for a static definition of the rings (i.e., same for every airport) by defining zones up to 20km in Appendix A.5.

Figure 7: Control group definition based on distances - Frankfurt Airport



Notes: Graphical representation of the control group definitions based on the distances between the airport building and the noise contour for the airport in Frankfurt.

Source: Authors' graph.

Table 7 shows that shrinking the control group distances (mean and median specifications) leads to larger effects. Expanding the distance to the maximum reduces its magnitude. Nevertheless, our baseline finding holds up to changing the control group definition. This test mitigates the concern that our main specification draws on apartments in the control group far away (or also exposed to noise) and thus, unsuited for comparison with the treatment group.

Table 7: Robustness - Change of control group definition

Dependent Variable:	log(apartment price)		
	(Mean dist.)	(Median dist.)	(Maximum dist.)
	(1)	(2)	(3)
Pandemic \times NoiseContour	0.033*** (0.005)	0.035*** (0.005)	0.016*** (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: 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 in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%. *Source:* Authors' table.

5 Conclusion

This paper studies the relationship between housing prices and aircraft-related noise. Identifying the effect of airport noise is a difficult task. Airports are large infrastructure projects. Their installation is publicly known long before the construction is completed. This evokes the issue of announcement effects in every setup, analyzing noise effects from the opening of new airports.

To bypass this challenge, we exploit the Covid-19 lockdown in March 2020 in Germany as the source of variation in air traffic and aircraft-related noise. Due to travel bans and closed borders, the aviation sector took a severe hit leading to a strong decline in flight activity. We use this reduction of aviation noise by applying a difference-in-difference approach. The study builds on a granular data set that takes exact geo-references of apartments and connects them to noise contour maps of German airports. We also control directly for an extensive list of covariates to identify the noise effect.

We show a positive effect on apartment prices once the unexpected event of silence occurs. The baseline results suggest a price increase of around 2.3% after the pandemic started. This indicates a catching-up process for treated apartments once the burden of extensive noise is relaxed. We also conduct several robustness checks to validate our findings. The results hold up to changes in the sample, the introduction of varying fixed effects, and changing the control group definition.

The heterogeneity analysis reveals an even larger effect for apartments that are affected by higher noise levels before the onset of the pandemic. Those apartments react stronger to the noise reduction than weakly affected apartments. Moreover, the effect is characterized by strong temporal patterns. During the mid-stages of the pandemic in 2021 the effect peaks at about 5% to 6%. Still, in the first quarter of 2022, we find significant effects which get insignificant in the second quarter of 2022. It remains unclear whether the aviation market in Germany will recover to its initial activity or if the noise-polluted areas will face a permanent lift of the noise-pollution. Thus, from a theoretical perspective, we cannot assess if a price effect is justified by long-term changes in noise exposure.

Still, our study contributes to the literature by showing that the absence of a disamenity (high noise exposure) leads to quick reactions in the housing market without price stickiness. As the peak of the effect does not persist over time, we even see that the housing market (in our example) tends to overreact to the elimination of disamenity in terms of exceeding prices (given the regeneration of air-traffic over time). Information asymmetries may explain those strong effects on the temporal improvement of noise reduction. Buyers who have never faced noise exposure may not be aware of future exposure when buying an apartment in the treated area. Mandatory disclosures may help to

prevent such information asymmetries.

In a broader context, the results can be transferred to the effectiveness of local environmental policy for urban planning. While most of the studies analyzing noise pollution exploit setups with increasing noise levels, we can show effects of lifting such noise pollution. Once the noise is expected to reduce, locations suffering from noise immediately catch up.

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A Appendix

A.1 House Prices and Apartment Rents

We also study the impact of the noise reduction caused by the pandemic on real estate prices (private houses) and apartment rents. We also combine sales data for houses and apartments in one specification. The RWI offers information on houses for sale (RWI, 2021c) and apartments for rent (RWI, 2021d). The data has the same structure as our main data set (apartments for sale).

Note that the included home characteristics vary slightly between houses and apartments for sale. For example, the estimation of house prices includes the house’s plot area and the number of floors. As this information is unavailable for apartments, only matching characteristics are included when both data sets are combined (column (2) Table A1). The estimation for apartment rents contains the same housing characteristics as the main specification but the dependent variable changes to the rent per square meter. All other controls are identical to previous settings. The methodology also remains the same.

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%.

We do not include either house sales or apartment rents in our main specification as 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 A1: Other housing types

Dependent Variable:	log(house price)	log(price)	log(rent per m ²)
Data:	HS	HS & AS	AR
	(1)	(2)	(3)
Pandemic \times NoiseContour	0.017*** (0.006)	0.022*** (0.004)	0.021*** (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: Baseline setting for houses for sale (HS) in column (1), the combination of apartments and houses 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 in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%. *Source:* Authors' table.

A.2 Clustering

Our main analysis uses robust standard errors. We assign the housing units on the individual level to the noise contour to define treated apartments. Further, the entire country is affected by the Covid shock and therefore, the noise reduction simultaneously. Still, one might argue that applying clusters is needed for this kind of analysis.

Table A2 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 A2: Robustness - Clustering

Dependent Variable:	log(apartment price)		
	(Grid) (1)	(Municipality) (2)	(District) (3)
Pandemic \times NoiseContour	0.023** (0.011)	0.023** (0.009)	0.023** (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: Regression output for various levels of clusters (grids, municipalities, and districts). *Pandemic* indicates periods after March 2020 and *NoiseContour* being equal to one for objects within the noise contour of major airports. Cluster standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.

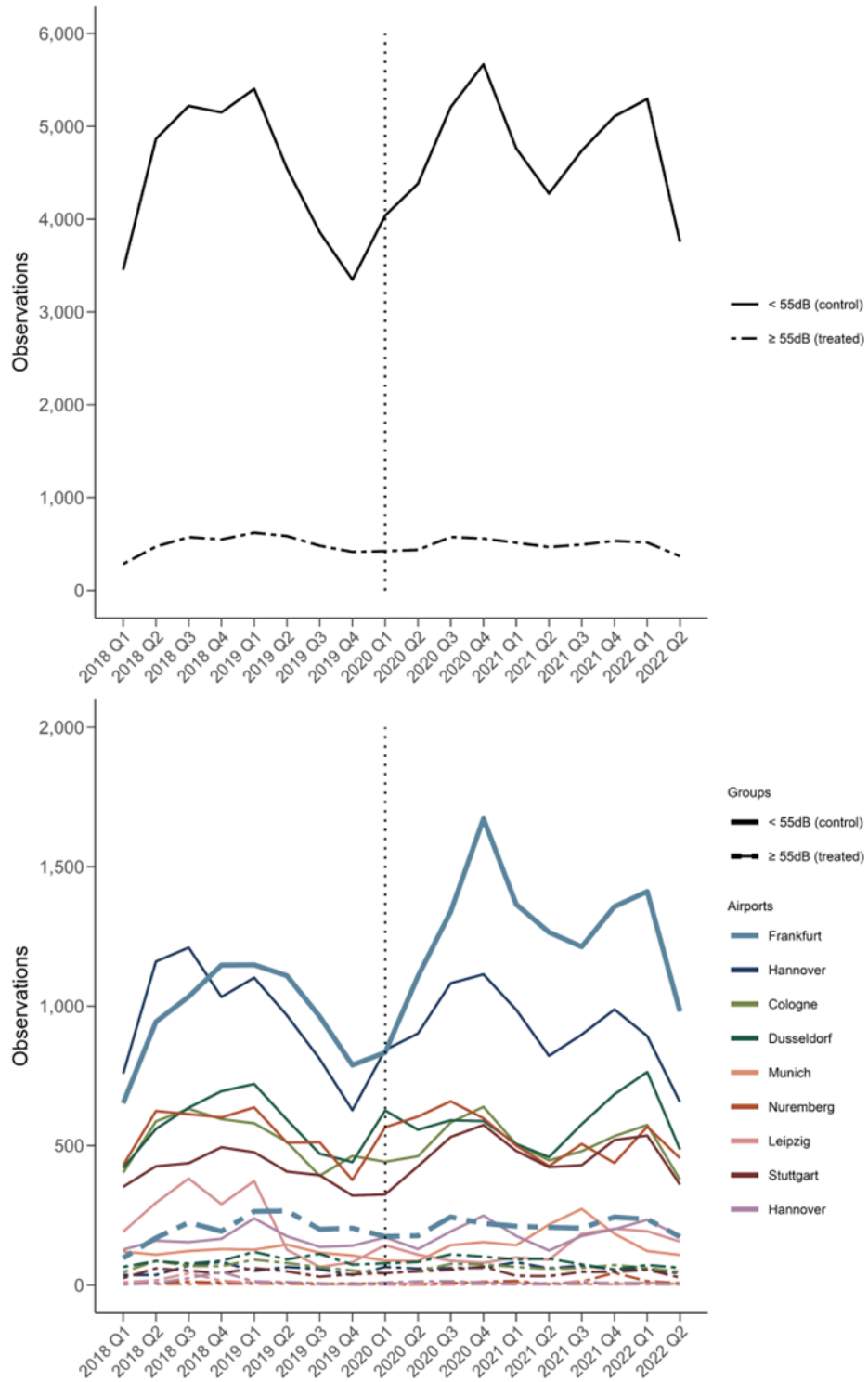
Source: Authors' table.

A.3 Number of observations

Figure A1 shows the number of observations over time by airport and treatment (dashed lines) and control group (solid lines). The control group combines more apartments than the treatment group (independent of the airport). The figure also points out that the number of observations increases during the start of the pandemic, especially for Frankfurt Airport (bold lines).

Note that the figure also reveals why a sub-analysis for individual airports is unreasonable. Even though being interesting, e.g., one could analyze the differences between passenger and cargo airports, the small number of observations for single airports prevents such an analysis.

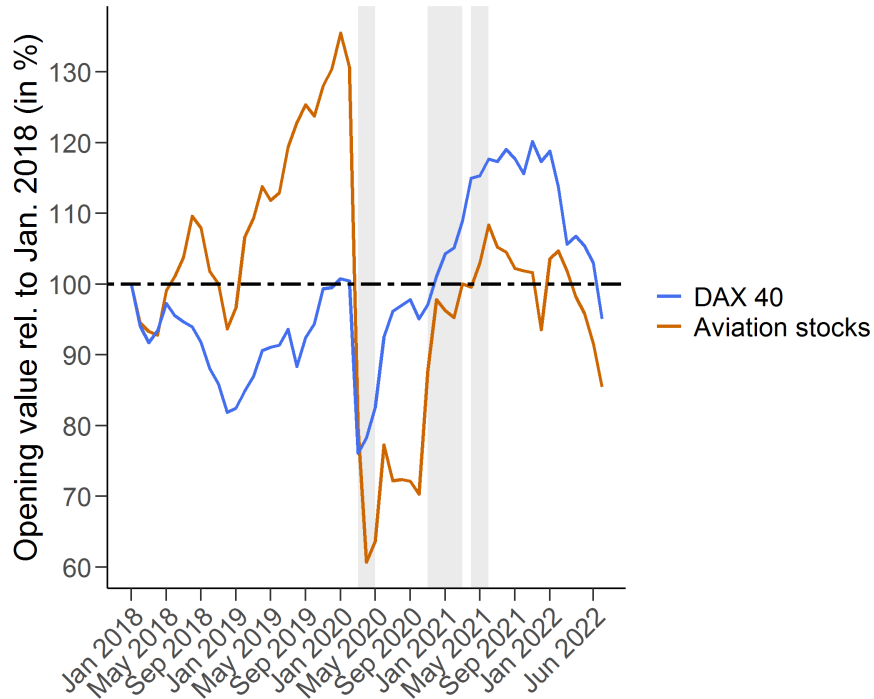
Figure A1: Number of observations by airport



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 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.

A.4 Stock market development in the aviation sector

Figure A2: Development of DAX 40 and aviation stocks



Notes: 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.

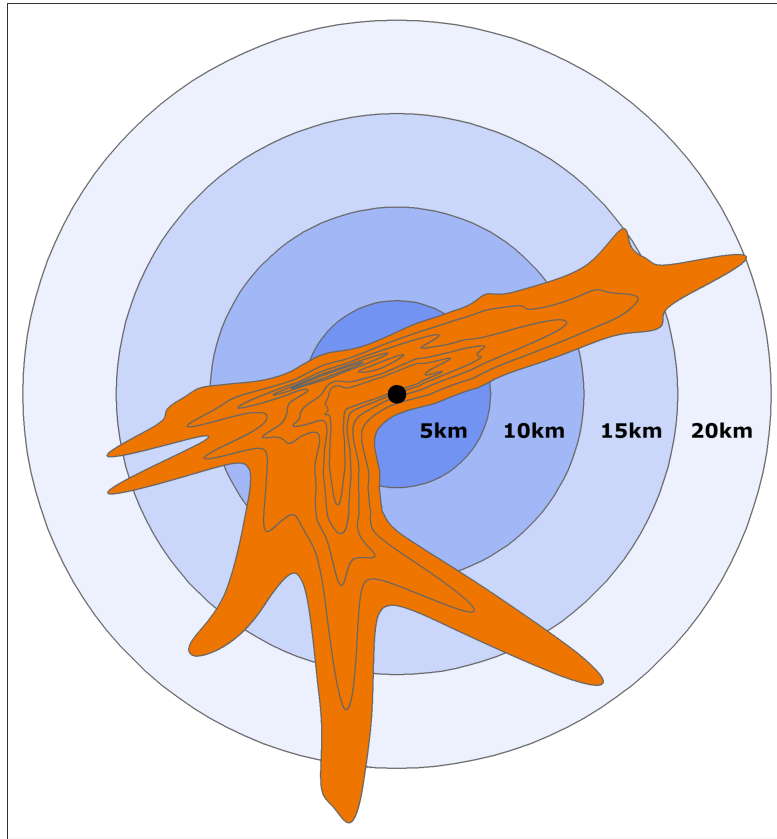
A.5 Additional Robustness Test

In previous settings, we define the control group as beyond the noise contour of the respective airport but limited to 5km (baseline) or restricted by distances based on the airport and the contour (robustness). We move away from this data-driven approach to define the control group and assume static distances from the airport for this additional test. We draw circles of 5km to 20km radius around the airport. Our control group represents the apartments within these areas but beyond the noise contour.

Note that these static distances are identical across airports. The previous measures based on the contour shape differ for each airport. Thus, these settings take the individual circumstances at each airport into account.

Figure A3 displays the circle definition of the Frankfurt Airport.

Figure A3: Control group definition based on distances - Frankfurt Airport



Notes: Graphical representation of the control group definitions based on the static distances around the airport in Frankfurt.

Source: Authors' graph.

Note that the neutral zone (1km around the noise contour) is also excluded in this setting.

Table A3 suggests that our results are robust to different definitions of the control group. The restriction to 5km and 10km show the same effects as the main specification. The other two distances have smaller effects.

Table A3: Robustness - Change of control group distance

Dependent Variable:	log(apartment price)			
	(Restr. 5km) (1)	(Restr. 10km) (2)	(Restr. 15km) (3)	(Restr. 20km) (4)
Pandemic \times NoiseContour	0.023*** (0.006)	0.023*** (0.005)	0.018*** (0.005)	0.016*** (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: Regression output with varying static distance measures for the control group. Column (1) restricts the control group to 5km, column (2) to 10km, column (3) to 15km, and column (4) to 20km around the airport building. *Pandemic* indicates periods after March 2020 and *NoiseContour* being equal to one for objects within the noise contour of major airports. Robust standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%.

Source: Authors' table.