Housing Prices, Airport Noise and an Unforeseeable Event of Silence – Airport Noise Decreases During the Covid Crisis

Authors: Philipp Breidenbach[+] and Patrick Thiel[+*]

[+] RWI, *RGS Econ

Abstract:

Starting in March 2020, the spread of Covid-19 caused fundamental societal changes and challenges. Besides a variety of negative effects of the pandemic, we focus on a specific side effect with partially positive impact. Due to the pandemic and the lockdown measures, the air traffic collapsed in March 2020. Residents, close by the airport who faced massive aviation noise pollution suddenly experienced “an event of silence”. We exploit this sudden decrease of noise to analyze whether the noise decrease affected housing prices for apartments located within the noise contour of German airports. To derive causal estimates, we exploit a two-way fixed effects model using apartments in the proximity of the airport. We argue (and empirically show) that the control regions do not differ from the treated ones. While the pandemic was initially expected to affect the noise level only temporarily, the course of the pandemic illustrated a permanent shock through, for example, the rise of virtual meetings. Our results strongly support our hypothesis. While there is basically no effect on apartment prices before the first lockdown, we observe a price increase of 3% after the lockdown when it became obvious that the aviation sector will not recover swiftly. The effect is even stronger in the first half of 2021 (5%). For those locations exposed to high noise levels (before the pandemic), the effect even peaks at 8%. The paper contributes to the literature in two ways: First, the change of pollution is truly exogenous without any announcement or selection problems which typically evolve in similar papers regarding disamenities and housing prices. Second, in contrast to most evaluation showing that the erection of a disamenity affects prices negatively, we show the opposite effect. Locations, which permanently suffered from pollution in the past, are able to immediately catch up again, once the pollution is alleviated. This is good news for urban planning since local environmental policies seem to be meaningful.

JEL: Q53, O18

Keywords: Covid pandemic, aircraft noise, apartment prices, hedonic function

1. Introduction

The effect of environmental pollution on housing prices is a prominent field in urban and regional economics. As housing prices reflect the value of living in a certain neighborhood, it is not only relevant with regard to the housing market, but it gives important insights on the reactions of people when being exposed to environmental pollutions.

Within the broad field of disamenities (including environmental pollutants), we focus on the effects of airport noise on housing prices. Recent literature of the past decade provides evidence in numerous studies on the substantial impact of airports and the linked pollutions on health (e.g., Boes et al. 2013 and Schlenker & Walker 2016) and well-being (Lawton & Fujiwara 2016). In our study, we use the first Covid-19 lockdown in March 2020 and the associated massive decrease in traveling and flights at German airports to evaluate the effects of reduced aircraft noise. Compared to many other studies in the literature, this approach has three key advantages.

First, the global lockdowns in the course of the Coronavirus pandemic could not be predicted, so we can clearly characterize the decrease in noise as an exogenous event. As the lockdown hit most economies and travel bans and closed borders are one of 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. Thus, unlike general changes in noise around airports, no announcement effects or other policy influences on the decline in noise are problematic for us and we can show that we are able to analyze substantial changes of the noise pollution.

Second, the different stages of the pandemic allow us to measure a decreased noise level over a longer period of time, with different expectations on future noise. Whereas in the first phase of the Covid pandemic there was an assumption that air traffic would recover to the old level as the pandemic was (quickly) overcome. Over the course of 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 will limit business flights in the long term) and the continued growth of government efforts to limit CO_2 emissions. With a view to avoiding emissions, domestic flights will also decrease significantly after the pandemic.

Third, almost all airports are affected by the pandemic[1] and thus we can analyze accompanying circumstances that lead to stronger or weaker effects. In addition, there is a special feature of German

[1] Airports that have particularly heavy cargo traffic are the least affected.

airports. In particular, the small regional airports in Germany had to cope with long-term losses even before the pandemic. Their future prospects after overcoming the pandemic are therefore very poor (individual airports, for example Frankfurt-Hahn or Paderborn, have already declared insolvency). In contrast, the major airports (such as Frankfurt, Munich and Dusseldorf) are very likely to see strong air traffic again after the pandemic. Our setup allows us to consider different intensities of noise reduction in both the temporal and spatial dimensions.

We build our analyses on a data set linking German apartment offers and contours of aviation noise surrounding German airports. The offer data are taken from the RWI-GEO-RED data set (described in Schaffner 2020) which comprises all offers from the German market leader in housing advertisements ImmoScout24. We focus on the data sets of apartments for sale. Using the 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). The merge of the data gives a very detailed impression on the noise pollution that affects the individual offers.

Given the detailed information for each apartment on noise pollution and time of the offer, we exploit a two-way FE model (on the location in a noise exposed area and the time before and after the onset of the pandemic) allowing us to identify causal effects of the treatment on the treated. The model follows the idea of a difference-in-difference analysis and the interaction of both fixed effects forms a treatment indicator. The treatment group is defined by all those apartments affected by severe aviation noise (above 55dB before the pandemic). In contrast, the control group comprises all apartments that are also located close to the airport in a surrounding of up to five kilometers but that are not affected by noise. This close geographical link ensures that both groups are affected equally by other developments in the pandemic (e.g., local lockdown measures or shocks of specific branches). Additionally, contradicting effects of the decline of flights (and noise) such as job losses at the airport or aligned businesses hit both groups equally. This focus on a geographically very restricted sample ensures that our analyses are able to detect pure noise effects.

The results clearly hint at effects of the noise reduction on housing prices. While there are basically no observable effects in the first months of the Covid-19 outbreak (marking the first lockdown in Germany), we observe an increase of apartment prices of about 3% during the summer of 2020. While this period is marked by a low incidence and rather lax restrictions, it revealed that the aviation sector does not recover quickly to the pre-crises level. We find the strongest effect for spring in 2021, which is also characterized by low Covid-19 incidences. Here, the positive effect increases to about 5%. Although, the noise-level at this time is considerably higher than during the strong lockdown period, the effect might illustrate a change of perceptions of residents that the pollution will remain lower permanently (compared to the pre-Covid-19 period). Within locations with priorly very high noise exposure, the effect peaks to about 8%.

Our study, therefore, approaches the relationship between housing prices and disamenities in reversed way compared to most other papers. We do not focus on evaluating a disamenity with the result that it impacts apartment prices negatively but we show a positive effect in absence of the same disamenity. This is an important contribution with highly real-world relevance because it hints at improvements of living standards once the burden is lifted. Policymakers might be keener to take actions to reverse disamenities if the positive effect of their removal has been shown.

2. Background: Airport Noise in the literature

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 or indirectly through numerous suppliers. Airports are also a central option for medium to long distance travel for most people. On the other hand, they are major pollutants in form of air and noise pollution. Therefore, airports represent a burden to those living close by. Before the Covid-19 pandemic unsettled the world, there was no sign of slowdown in the aviation business which led to an ever-increasing trend in air traffic in most countries.

The ambiguity of airports can also be found in the academic literature. Nelson (2004) finds a negative relationship between air traffic-related noise and housing prices in his meta-analysis. Jud & Winkler (2006) add to this finding by suggesting a negative effect of the announced expansion of the Greensboro airport in North Carolina.

In contrast to these negative effects, Brueckner (2003) finds a positive effect of employment and Tomskin 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 your neighborhood.

Focusing on only one aspect does not account for the multiple dimensions involved when studying airport noise. An argument that was stressed, for instance, by Espey & Lopez (2000), Lipscomb (2003), Cohen & Coughlin (2008, 2009), and Ahlfeldt & Maennig (2010). Cohen and Coughlin (2008, 2009) and Lipscomb (2003) suggest that the negative noise effects cannot be countered by the positive effects of employment or proximity.

Most studies focus on house prices instead of apartments to evaluate airport noise. One exception is Boes & Nuesch (2011) who 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 noise increase. Baranzini & Ramirez (2005) find a similar effect (1% per decibel 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 decibel in apartment prices. So, the results from the rental apartments seem to be relatively small compared to objects from the buyers' market. This might be reasonable as different expectations led to the decision of buying or renting an object. As renter are expected to live at one location for a shorter period, they would benefit less from noise reductions. Buyers, on the other hand, are supposed to stay in one place for years or decades and therefore, they appreciate an improvement in environmental noise more. An argumentation presented by Ahlfeld & Maennig (2015) who evaluate the perception of homeowners and renters regarding the proposal to build the new airport Berlin-Brandenburg and to close the old Berlin-Tegel.

Due to this duality pointed out in the literature, identifying causal effects needs to be given special attention (Breidenbach 2015). Since airports are such large infrastructure projects, their location does not change suddenly and even extensions are known publicly. They are planned and built over an extensive period and their location is known long before they are completed. This introduces the challenges of announcement effects and simultaneity between airport noise and housing prices. When the location becomes public and is not chosen randomly which is almost exclusively true, then the regions' population will react to the positive and negative effects in advance. This also applies for the housing market.

By focusing on the first Covid lockdown as variation source in air-related noise, we are able to analyze the effect of airport noise on apartment prices without being concerned about announcement effects. The Covid-19 crisis could not have been anticipated neither by airport operators nor by residents close by.

3. Empirical Setup & Data

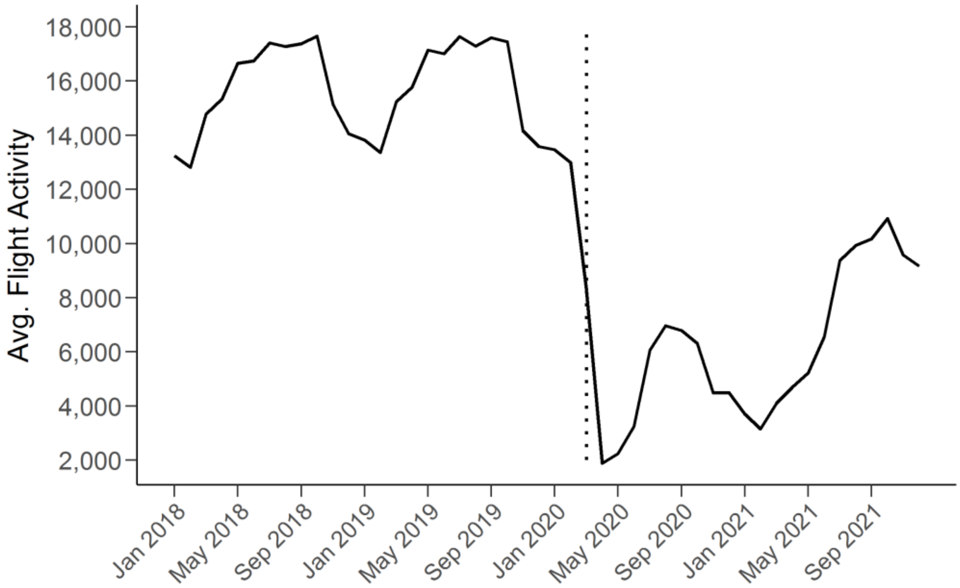
Our data base combines two main sources. We use the RWI-GEO-RED data which offers listings of apartments for sale made available on ImmoScout24.de. We link this data with noise contour maps of major airports (see Figure 6 for an example of such a map). These maps define areas around airports and their runways where aircraft noise is a burden to the local community. Intersecting both data sets allows us to determine the noise level of each apartment.

We aim at estimating the causal effect of airport noise on apartment prices via empirical microeconometric methods. Thereby, the lockdown measures in the course of the Covid-19 pandemic serves as a natural experiment that provides exogenous variation in the exposure to aviation noise pollution. Due to the lockdown, the flight activity at German airports decreased, causing a substantial reduction in the noise pollution of apartments surrounding the airport being treated by noise for many years and decades before.

This decrease is meticulously documented by the number of flight activities[2] at German airports in the course of the years 2018 to 2021 (see Figure 1). 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. Despite to the years before, the 2020's peak during vacation time in August only climaxed at about 7,000 activities (in contrast to 17,000 before the pandemic) and still only peaks at about 11,000 flight activities with much less restrictive travel bans in 2021. 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 development of flight activities and noise exposure of surrounding inhabitants) is hard to foresee.

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

Figure 1: Average flight activity over time

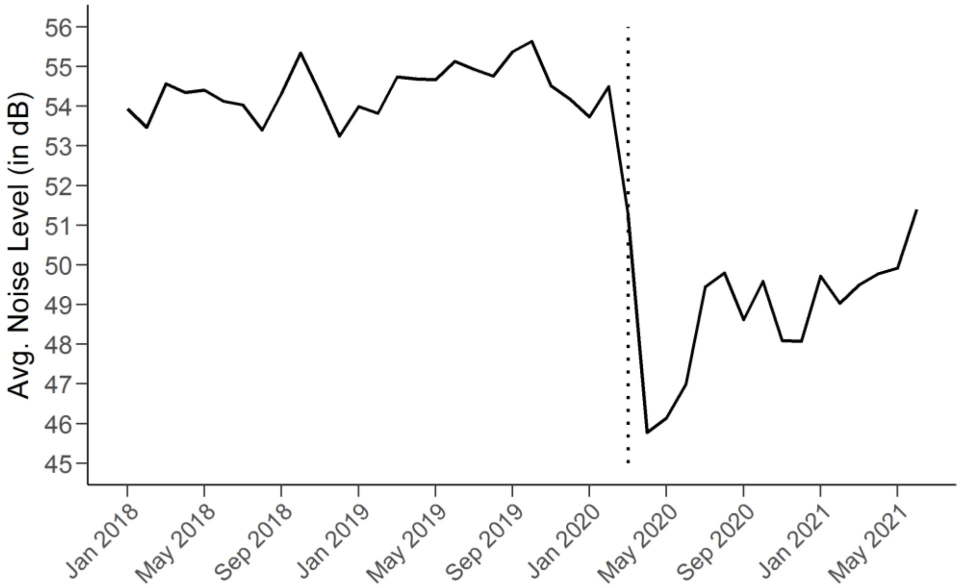


Note: Average flight activity over time which includes starts and landings. The vertical line (dotted) represents the first lockdown in March 2020 which is interpreted as start of the pandemic in Germany.
Source: Authors' graph.

The reduction of flight activity during the pandemic is also translated into a decrease of air traffic-related noise. Figure 2 shows the average noise level[3] over time across major airports. The data is provided by the airports themselves and is based on measuring stations located close to the airports and their runways. The noise level fluctuated between 54dB and 55dB in pre-Corona times and stabilized on an average level of 54.5dB. After the first lockdown became apparent the noise level dropped heavily to almost 45dB in April 2020. Afterwards the noise level recovered slightly, as did the flight activity, but the average of this period under treatment is 49.5dB and hence, still 5dB below the one of the pre-treatment period. 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 lockdown is, therefore, not just documented in summary statistics but is also highly detectable by ear. So, a similar pattern as for the flight activity can be observed. This amplifies our argumentation that the COVID pandemic led to a reduction in aircraft-related noise which impacts apartment prices in the proximity to airports.

[3] 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.

Figure 2: Average noise level over time



Note: Average noise level over time as measured by the Day-Evening-Night level (LDEN). The dotted line represents the first lockdown in Germany.
Source: Authors' graph.

Establishing a setup that allows causal inference of one specific shock is particular tricky. The pandemic and the lockdown measures affected the economy and the society in various areas. Thus, our identification strategy needs to allege strong arguments, proving that the pandemic might have assailed our treatment group via other channels than the aviation noise. Simultaneously, it needs to be shown that aviation noise is the only effect of the pandemic that impacted the treatment group differently in contrast to a specific control group. We focus on a highly geographically restricted area with control and treatment group being in close proximity to each other to avoid differences other than the noise reduction.

To emphasize this argument, we use the RWI-GEO-GRID data set to compare the control and treatment group in key (economic) characteristics. The RWI-GEO-GRID offers these characteristics (like purchasing power and population) on a one square kilometer grid for the whole of Germany. The data is original provided by microm GmbH and a detailed description of the data can be found in Breidenbach & Eilers (2018). The analysis is based on the latest year, 2019, covered in the data. We turn to three groups of variables: demographics (including the number of households and the number of people per grid cell), household composition (with the share of single, couple and family households), and socioeconomic factors like the household purchasing power (measured in Euro and per year) and the unemployment rate (in percent) in the respective grid. Further, the summary statistics, which can be found in Table 1, are calculated for the control and treated regions separately.

Treated grid cells are all those that are within the noise contour of main airports. Figure 6 shows such a contour map for the airport in Hamburg. The control region lies beyond the contour and is restricted to a buffer of five kilometers around the contour. Note that we exclude grids that are within a one-kilometer buffer around the noise contour. The intention is to rule out grids that might be both treated and non-treated at the same time.

Table 1: Comparison treatment and control group

	Control region		Treated region	
Variables	Mean	SD	Mean	SD
Demographics				
Number of households	967.65	1726.90	683.48	1205.41
Number of people	1815.16	3075.94	1346.98	2370.48
Household composition				
Share of singles (in %)	36.10	26.40	35.28	27.03
Share of couples (in %)	36.06	27.54	33.67	27.90
Share of families (in %)	27.84	26.20	31.05	28.16
Socioeconomic factors				
Household purchasing power	50685.71	10425.33	50081.01	10774.33
Unemployment rate (in %)	4.66	3.37	4.85	3.52

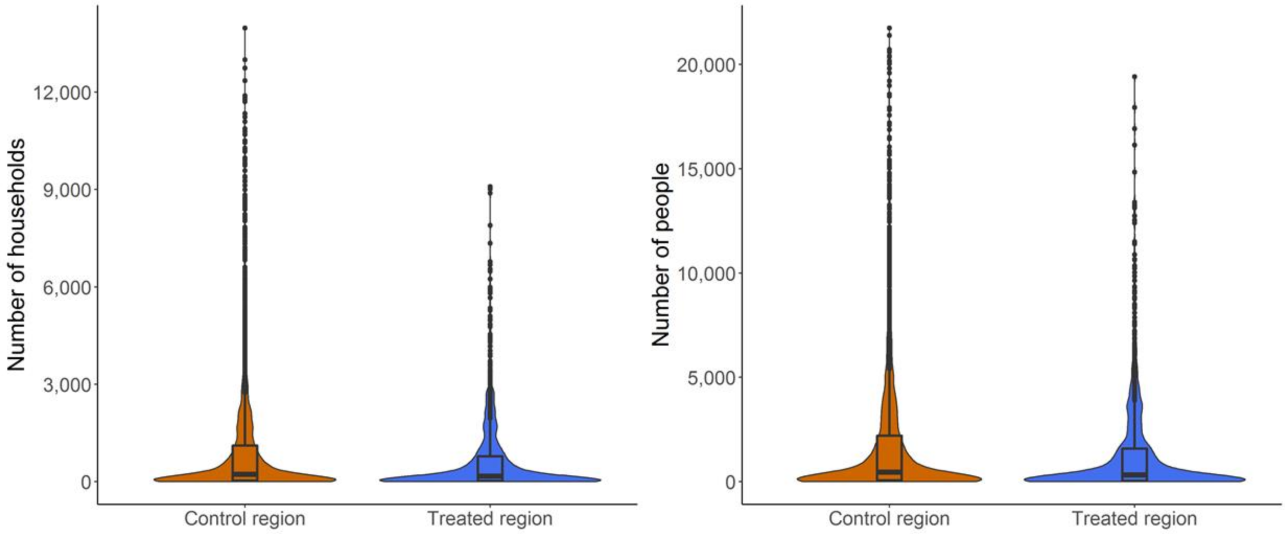
Note: Summary statistics (mean and standard deviation (SD)) to compare the control and treated region. The first group consists of grids beyond the noise contour and the latter is formed by grids within the contour.
Source: Authors' table.

The demographics show that control and treated regions slightly differ in how many people and households live in the respective grid cells. This difference in means, however, does not carry over to the household composition. Here, both groups show similar shares of singles, couples and families with family households representing the least present group. The household purchasing power and the unemployment rate are comparable as well.

To supplement these summary statistics, we also plot the distribution and the boxplot of each of these seven key characteristics using violin graphs. The results can be found in Figures 3-5.

Figure 3 shows the distribution of the demographics, i.e., the number of households (left panel) and the number of people (right panel) living in the control and treated regions. While the control group reaches higher extrema in both variables, the shape of the distribution is similar between both groups. There is a large number of grids with very few households/ people in both categories with the majority of grids being covered up to 3,000 households or 5,000 people.

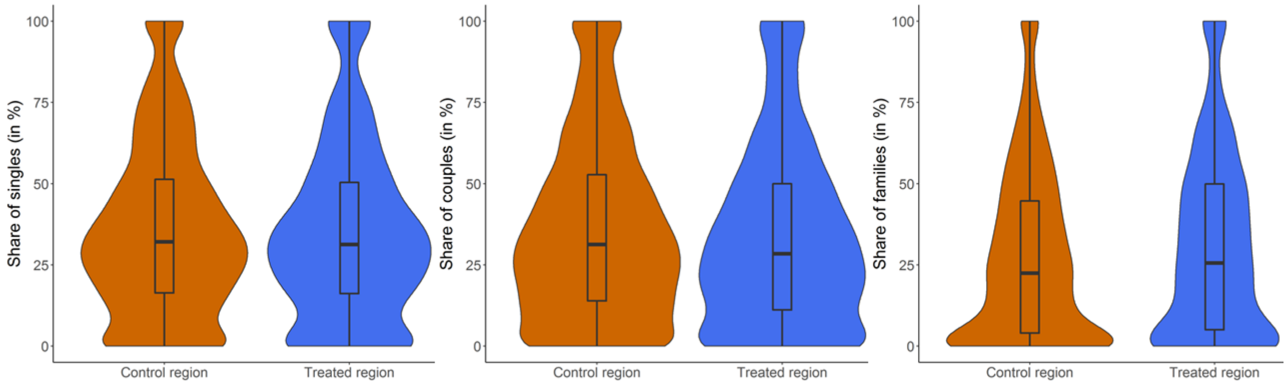
Figure 3: Distribution and boxplot of demographics



Note: Distribution and boxplot of number of households (left panel) and number of people (right panel) for the control and treated regions.
Source: Authors' graph.

The distributions for the household composition, displayed in Figure 4, reestablishes these similarities between both regions. Single households are the most common form of living arrangements among the three groups as the bulk of grids register an average share of 35% for single households. The share of couples (center panel Figure 4) is evenly distributed between zero and the average. The distribution tightens afterwards. As for the other two household groups, the control region reveals higher average values. Lastly, the share of families is, on average, the least present group among the household composition.

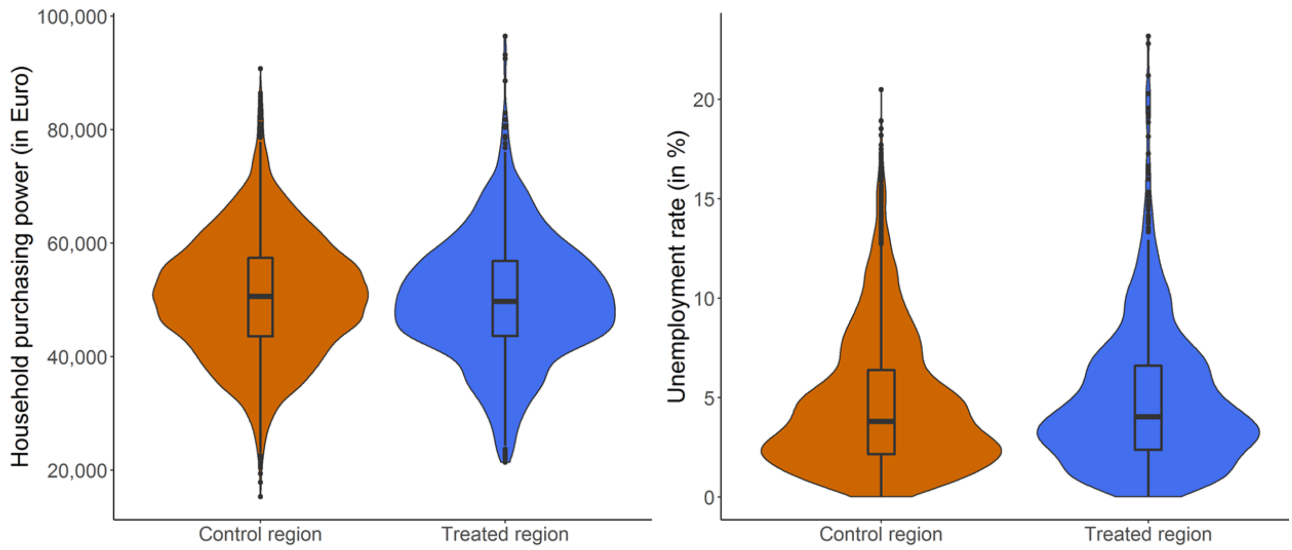
Figure 4: Distribution and boxplot of household composition



Note: Distribution and boxplot of share of singles (left panel), share of couples (center panel) and share of families (right panel) for the control and treated regions.
Source: Authors' graph.

Figure 5 presents the distribution of the household purchasing power and the unemployment rate. The purchasing power is strongly distributed around its average values in both regions (approximately 50,000 Euro per year). The tails are less occupied. For the unemployment rate, the majority of the grids have values between 0% to 5% regardless of the region. The treatment region seems to have more grids with higher unemployment rates leading also to the larger average shown in Table 1.

Figure 5: Distribution and boxplot of socioeconomic factors



Note: Distribution and boxplot of household purchasing power in Euro (left panel) and unemployment rate in percent (right panel) for the control and treated regions.
Source: Authors' graph.

Overall, the summary statistics and the distributions of the grid cells of the treated and control regions paint the picture that both groups are similar in key (economic) characteristics leading to the conclusion that we compare similar objects in our setting.

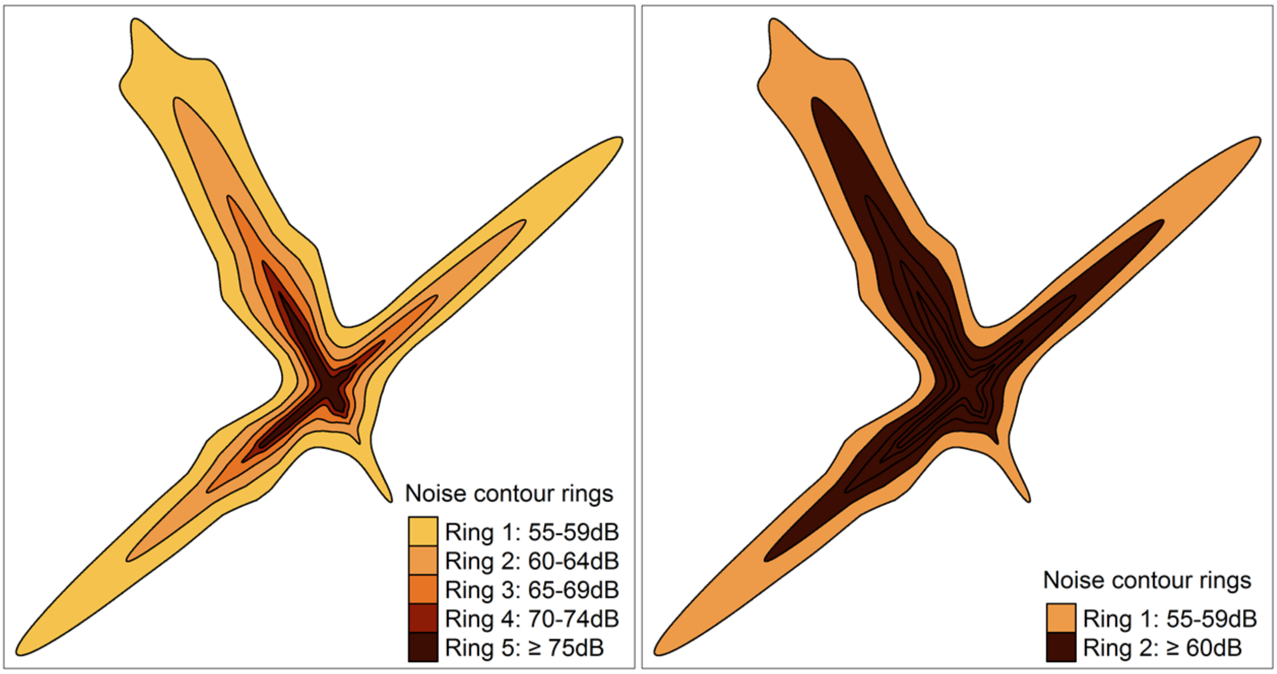
Before discussing the empirical strategy, the used data should be described. We build on several sources to construct a data set that allows us to test the hypothesis that the reduction in aircraft noise during the Coronavirus pandemic is translated into a change in apartment prices close to airports. Further, the detailed data structure enables to conduct an empirical strategy on a small-scale regional level.

The RWI-GEO-RED serves as a source for the apartment data which provides individual apartment prices on a monthly level. The base for this data set are offers listed on the real estate website ImmoScout24.de. It comes with a large list of object characteristics (like the size of the object, number of rooms and indicators, for instance, for having a garden or balcony). Additionally, the data is available at the individual object level meaning that the precise geographical location of each object is known. This is crucial as we connect the housing data to the nearest airport based on spatial information of the noise contours.

We exclude objects with characteristic values below and above the 1 and 99 percentiles during the data cleaning process. The aim is to avoid unrealistic values due to fake listings and typing mistakes on ImmoScout24. The observation period is January 2018 to June 2021. We also drop any apartment offers from March 2020 as this is the month the first lockdown happened. As the apartment data is given on a monthly level, we would otherwise include objects that are partially treated and non-treated at the same time. A detailed description of the apartment data can be found in Schaffner (2020).

The second data source is provided by the Federal Environmental Agency (FEA 2019a) which offers noise maps of airports. These contour maps define zones around airports and their runways to indicate areas of particular exposure and they are the outcome of the European directive of the assessment and management of environmental noise. The resulting noise intervals typically range from 55dB to above 75dB. Hence, they assume that aircraft noise below 55dB does represent a special burden. Figure 6 shows such a map for the airport in Hamburg. The smaller the distance to the airport and its runways is, the higher is the noise level. 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 6: Noise contour map of Airport Hamburg



Note: Noise contour map of the airport in Hamburg. The left panel shows the noise intervals as displayed in the original data. The right panel represents the noise intervals as used in the analysis.
Source: Authors' graph.

Our setting is restricted to main airports in Germany. The Federal Office of Statistics (FOS) defines airports which have at least 150,000 flight guest units[4] per year as major airports. This results in 23 main airports in Germany for the year 2021. These airports made up 99 percent of Germany's volume of the transport of passengers and goods carried through the air 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 air traffic movements, only eleven maps are available. From these eleven two are located in Berlin. We exclude Berlin completely from the analysis for two reasons: First, Berlin possessed two airports for a long time – Berlin-Tegel 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 building 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 airport Berlin-Schoenefeld such that 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

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

are excluded. The second reason arises from the decision to control the development of rents in Berlin. In 2020, the Berlin Senate agreed to counteract the dramatic increases in the city's rent. They established a rent limit (in German: Mietpreisbremse) with the aim to stabilize the rent level for the next five years. This regulation was lifted by the Federal Constitutional Court in 2021. So, similar to the airport situation, there is some uncertainty involved on 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. We are studying the impact of noise reductions on apartment prices. A policy measure like controlling rents prevents the free development on the housing market. Our estimates, therefore, might be compromised if Berlin would be included in the sample.

We arrive at with nine major airports which are depicted in Figure 7. Even though only nine of the originally 23 major airports are included in the study, these airports cover a substantial amount of the 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 7: Locations of major airports

Note: Locations of major airports included in the analysis.
Source: Authors' graph.

We complement our data set by adding additional controls. First, the straight-line distance (Euclidean distance) to the nearest regional centers is included as 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, BBSR defines municipalities of regional importance leading to the classification of large, medium and small centers. The aim is to ensure equal living conditions even for remote locations (see Friedrich et al. 2021). These centers provide a wide variety of services to the local community ranging from shopping opportunities, leisure activities, transportation infrastructure but also health and administrative services. The type of service and degree of specialization depends on the size of the regional center. Large regional center, for instance, offer education at the highest level with opportunities to visit universities, specialized libraries but also different kinds of museums. On the other hand, medium centers ensure a broader education lacking this specialization (see Einig 2015). Further, the large and medium centers are in particular important locations for working and represent business centers (Friedrich et al. 2021). They can also be interpreted as stabilizing factor especially in remote areas (Milbert & Furkert 2020). We are, therefore, aiming at controlling directly for the interdependence between regions by including the distances to these regional centers. Additionally, commuting plays a central role for many households, which in turn impacts housing prices and by adding these variables to the analysis we directly control for this relationship.

As second additional control variable, we implement the Euclidean distance to the airport building itself in our model. Airports cannot only be interpreted as disamenity due to noise and air pollution but they are also a working place either for people directly working at the airport or for suppliers located close by. They also offer travelling opportunities for medium to long distance travels. Without a covariate capturing this positive effect our estimates would be biased (see also literature discussed at the beginning). The geographical information is provided by FEA (2021) which offers a data set with all worldwide registered airports on openflights.org. This can be then linked to the geographical locations of the apartments.

We further add the Euclidean distance to major railroads to the regression model. The data is also provided by the FEA (2018) for the year 2017 and consists of all railroads that register at least 30,000 train movements per year. Similarly, we use the same data source to include the distance to major industry plants in agglomeration areas (FEA 2019b). Adding these additional noise sources allows us to control for their negative noise effect on apartment prices. Therefore, the estimates presented later reflect the aircraft-related noise effect. Note that all included distances are calculated in kilometers.

Table 2 provides the summary statistics for the object characteristics and the discussed additional control variables. It is divided into treated objects, i.e., those that are within the noise contour and therefore, exposed to aircraft noise, and control objects which are not extensively affected by air traffic-related noise. The table also indicates the summary statistics before and after the first lockdown (March 2020).

Table 2: Summary statistics

	Treated		Control	
	Before lockdown	After lockdown	Before lockdown	After lockdown
Price (in Euro)	313,203.9	376,018.1	363,572.4	460,355.9
	(196,627.8)	(219,304.6)	(260,088.9)	(305,835.8)
Size	86.399	85.666	82.666	83.944
	(31.329)	(30.64)	(32.104)	(32.912)
Number of rooms	2.942	2.968	2.845	2.89
	(0.969)	(1.002)	(0.998)	(1.033)
Age	37.367	48.734	47.778	55.314
	(20.994)	(28.011)	(31.442)	(33.807)
Endowment	2.409	2.411	2.364	2.399
	(0.601)	(0.612)	(0.597)	(0.604)
Bathrooms	1.164	1.189	1.143	1.17
	(0.383)	(0.403)	(0.367)	(0.397)
Floor	2.03	2.02	2.37	2.458
	(1.455)	(1.444)	(2.317)	(2.635)
Heating type	10.176	10.111	9.982	9.682
	(3.969)	(3.93)	(4.111)	(4.175)
Condition	5.111	5.272	5.419	5.171
	(2.581)	(2.472)	(2.36)	(2.471)
Balcony	0.812	0.774	0.767	0.762
	(0.391)	(0.418)	(0.422)	(0.426)
Garden	0.189	0.194	0.178	0.181
	(0.391)	(0.396)	(0.383)	(0.385)
Built-in kitchen	0.342	0.377	0.401	0.393
	(0.474)	(0.485)	(0.49)	(0.488)
Dist. small regional center	10.579	10.397	9.848	9.591
	(7.307)	(7.727)	(6.134)	(5.87)
Dist. medium regional center	5.297	5.732	7.458	7.301
	(2.75)	(2.968)	(3.507)	(3.455)
Dist. large regional center	8.706	8.313	7.883	7.492
	(4.917)	(4.595)	(5.66)	(5.584)
Dist. airport building	9.636	9.636	9.711	9.761
	(4.475)	(4.604)	(4.606)	(4.737)
Dist. railroads	1.247	1.19	1.134	1.105
	(1.089)	(1.138)	(1.223)	(1.231)
Dist. industry plants	4.431	4.439	3.649	3.706
	(3.006)	(3.385)	(3.837)	(4.049)

Note: Mean and standard deviation (in parenthesis) of the used variables for treated objects (i.e., within the airport noise contour) and control objects (beyond noise contour) and before and after the lockdown (March 2020).
Source: Authors' table.

We use the spatial information of the noise structure around the main airports and link it to the location of the apartments. Doing this allows us to define the treated group by those objects that are situated within one of the rings of the contour maps. The original noise contour data typically consists of five rings (as illustrated in left panel of Figure 6) but due to the low number of observations within the innermost rings, we define instead two noise intervals: one above 55dB and one above 60dB[5]. The right panel of Figure 6 displays this classification graphically. This difference in noise intensity is later used in one of the heterogeneity analyses. The control group is then formed by apartments beyond the outermost ring but within a five-kilometer buffer around the contour shape. We exclude control objects within a one-kilometer buffer around the noise contour. This neutral zone ensures that there are no objects in the control group which are partially treated by air traffic-related noise. Otherwise, it would blur our estimated treatment effect. Note that we show this in one of the robustness checks where we explicitly include objects of the neutral zone in the sample.

This approach leads to the following number of observations for treated objects. Table 3 displays these by noise ring but also for the periods before and after the lockdown.

Table 3: Number of treated objects

	Before lockdown	After lockdown
Ring 1_{low}: $\geq$ 55dB	3,689	2,470
Ring 2_{high}: $\geq$ 60dB	657	459
Noise contour total	4,346	2,929

Note: Number of objects within the noise rings of the airports (i.e., treated objects) before and after the lockdown (starting March 2020). Ring 1 indicates areas with low noise (above 55dB) and Ring 2 reflects regions with high noise levels (above 60dB before the pandemic).
Source: Authors' table.

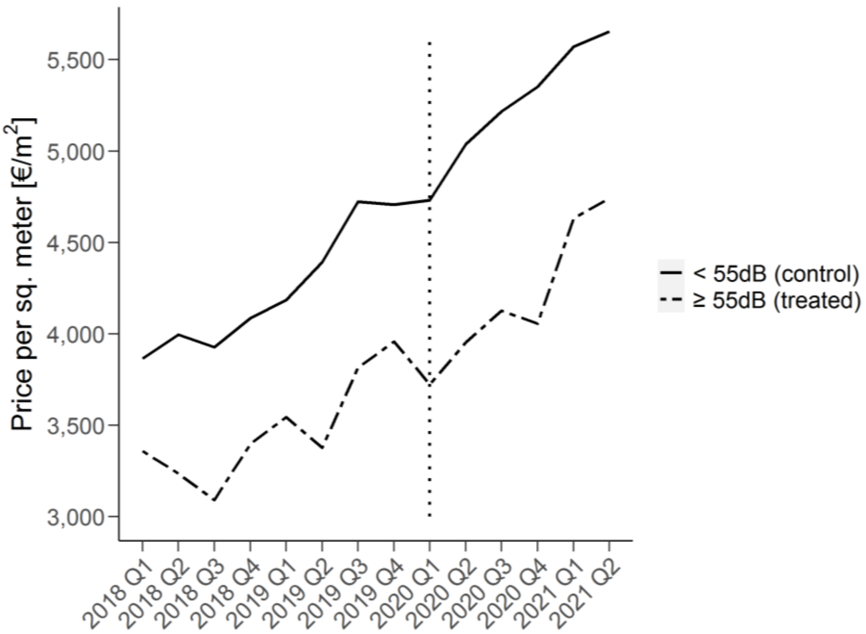
As we are estimating a two-way fixed effects model with a difference-in-difference layout, the development of prices before the shock occurs is a central issue of the identification. Figure 8 shows the average price per square meter (in Euro) by quarter. Three observations can be made from this figure: First, both the control and treatment group follow an upward trend in prices. At the beginning of our observation period, prices ranged between 3,000 and 3,500 €/m^2 for treated objects and just below 4,000 €/m^2 for control objects. In the second quarter of 2021 prices have risen to around 4,500 €/m^2 for treated and to 5,500 €/m^2 for control objects. This is an extensive increase in prices over a

[5] Note that these noise levels refer to pre-Covid times (prior March 2020). Following the pattern presented in Figure 2, the actual noise during the pandemic is much lower.

relatively short period of time. The second observation is that the treatment region performs worse in price than the control group at any given time. The figure suggests that objects closer to airports which are exposed to higher noise levels can be sold, on average, for less. Lastly, the price curve of the objects within the noise contour (treated) looks relatively bumpy compared to the control region. This results from the lower number of observations in the treatment group as housing data and average price fluctuates over time quite strongly.

Note that Figure 8 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 object characteristics. Our robustness checks suggest that when controlling for the discussed covariates there are no effects prior to the first lockdown.

Figure 8: Price developments by quarters



Note: Prices per square meter by quarter for treated objects (within the noise contour and exposed to at least 55dB of air traffic noise) and control objects (beyond noise contour and a noise level below 55dB). The vertical line represents the first Coronavirus lockdown (March 2020).
Source: Authors' graph.

For the empirical strategy, we estimate a two-way fixed effects model of 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 on the following form:

$$y_{itg} = \beta \boldsymbol{X}_{itg} + \delta NoiseContour_{ig} + \gamma\left(1^{st} Lockdown_t \text{ x } NoiseContour_{ig}\right) + Month_t + Grid_g + \epsilon_{itg}$$

The dependent variable, y_{itg}, represents the logarithm of the offering price apartment i, in month t and grid cell g. $\boldsymbol{X}$ summarizes the control variables including the object characteristics, the distances to large, medium and small regional center, and the distance to the airports themselves, the distance to railroads and the distance to industrial plants. *NoiseContour* is the treatment indicator whether or not an object lies within the noise contour of a major airport which means that the object is at least exposed to an air traffic-related noise level of 55dB. So, for the control objects, the variable takes on the value of one if this is the case and zero otherwise. These control objects are restricted to a maximum distance of five kilometers from the border of the noise contour. Further, all control objects within a one-kilometer buffer around the noise contour are excluded. This neutral zone drops all objects 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. Neglecting this issue would dilute our treatment effect. We relax this setting in one of the robustness checks and incorporate the neutral zone in the sample.

Treated objects should benefit from the reduction in flight activity during the pandemic. On the other hand, control objects beyond the noise contour are not exposed to aircraft-related noise extensively, as their noise level ranges below 55dB. So, they are not supposed to benefit from the drop in noise level due to the Coronavirus pandemic.

The variable *1^{st} Lockdown* is a dummy variable which is equal to one for periods after March 2020 and zero prior to that. The first lockdown is used here because of its massive impact on the flight activity in Germany (see Figure 1). Even though Covid-19 cases were registered before this month, the aviation industry took a severe shock following the restrictive travelling rules due to the lockdown. To estimate the effect of the resulting noise reduction after the lockdown was in place, we implement the interaction term *1^{st} Lockdown x NoiseContour* which combines the lockdown dummy and the previously described noise indicator. Therefore, the coefficient γ is our main coefficient of interest and it gives us the additional effect on apartment prices for objects closer to the airport (i.e., within the noise contour) compared to those objects that are further away after the first lockdown (March 2020). It is an evaluation of the noise reduction due to the decrease in flight activity caused by the Covid-19 pandemic. We are able to identify this effect because of the regionally restricted area such that we can assume that the control and treatment group are comparable and affected by all other factors equally beside the noise level reduction.

To completement this small scale setting even further, we introduce regional and time fixed effects on the grid and monthly level to control for invariant factors. The regression is performed with robust standard errors.

4. Results

The presentation of our results is structured as follows. First, we exploit our model in the baseline specification (model 1) for the whole set of observed airports and for the full period of the pandemic. We further shed light on the heterogeneity of the basic findings. To test the robustness of our results, we finally provide a set of robustness checks.

Table 4: Baseline results

Dependent Variable:	log(flat price)
1^{st} Lockdown × NoiseContour	0.028***
	(0.005)
Full set of controls	Yes
Fixed-effects	
Months	Yes
Grids	Yes
Fit statistics	
Observations	71,608
R^2	0.91245
Within R^2	0.80718
Heteroskedasticity-robust standard-errors in parentheses	
*Signif. Codes: ***p < 0.01, **p < 0.05, *p < 0.1*	

Note: Baseline results with *1st Lockdown* indicating periods after March 2020 and *NoiseContour* being equal to one for objects within the noise contour of major airports.
Source: Authors' table.

Our baseline results support our hypothesis. The unexpected but substantial reduction of noise pollution positively affected those flats, exposed to aviation noise. After the lockdown (causing the reduction of noise), the offer price for those flats increased by 2.8% in contrast to the flats in the control group which are not exposed to noise but also located close to the respective airports. The effect is highly significant at the 1%-level using robust standard errors on the grid level.

Heterogeneous Effects

Time intervals

We study the effect for different stages of the pandemic. This time split especially follows the hypothesis that the perception on the development of future noise pollution have changed substantially during the course of the pandemic. While the initial German lockdown for six weeks in spring 2020 gave hope that the pandemic will affect the society hard but very shortly, this perception was more and more outdated during the summer of 2020. Although Germany managed to keep infection rates very low, the outbreaks in other countries clearly hint to the point that Covid-19 will not be over after a short lockdown. Additionally, the aviation market gave strong signals for substantial changes. On the demand side travel restrictions and the rise of virtual meetings indicate strong changes. Additionally, the bankruptcy of the airports Frankfurt-Hahn and Paderborn as well as the necessary billions of financial aids to Lufthansa (as largest airline in Germany) indicate similar disrupt shocks on the supply side.

To analyze different effect during the time intervals of the pandemic, we split the post-lockdown period into intervals of three months. The first interval (April to May 2020) consists only of two months as March 2020 is excluded from the study to avoid any confusion between treated and non-treated apartments. The period indicators are then interacted with the dummy stating proximity to airports (*NoiseContour*). Table 5 reports the results of these interaction terms.

Table 5: Heterogeneity Effect – Time intervals

Dependent Variable:	log(flat price)
Apr-May 2020 × NoiseContour	-0.005
	(0.013)
Jun-Sep 2020 × NoiseContour	0.028***
	(0.008)
Oct-Dec 2020 × NoiseContour	0.009
	(0.009)
Jan-Mar 2021 × NoiseContour	0.041***
	(0.011)
Apr-Jun 2021 × NoiseContour	0.047***
	(0.009)
Full set of controls	Yes
Fixed-effects	
Months	Yes
Grids	Yes
Fit statistics	
Observations	71,608
R^2	0.91247
Within R^2	0.80722

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***p < 0.01, **p < 0.05, *p < 0.1*

Note: Baseline regression for different periods of the pandemic. *NoiseContour* indicates treated objects (i.e., within the noise contour).
Source: Authors' table

To analyze different effect during the time intervals of the pandemic, we split the post-lockdown period into intervals of three months. The first interval (April to May 2020) consists only of two months as March 2020 is excluded from the study to avoid any confusion between treated and non-treated apartments. The period indicators are then interacted with the dummy stating proximity to airports (*NoiseContour*). Table 5 reports the results of these interaction terms.

The results from the time split clearly reveal temporal dynamics in the effects on housing prices. As expected, the initial lockdown period (April-May 2020) did not cause any effects on apartment prices. This may be caused by the general perception that the measures against Covid-19 will have a foreseeable end. The effect peaks during the summer period from June to September 2020 where many national restrictions were lifted but air-travelling still did not recover to the earlier level. Here we see a price effect of 2.8% which is strongly significant at the 1%-level.

Starting in 2021, the effect even increases to 4% (in the period January to March) and nearly 5% between April and June. Although, the number of flights was recovering at this time (to a lower level than before the pandemic), we observe the strongest effect at the end of the observed period. This may be caused by the perception of residents (and people moving into such exposed neighborhoods) that the aviation market will not fully recover.

Heterogeneity Effect – Noise levels

We exploit the richness of our data in this heterogeneity test by dividing the noise contour into two rings. 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 can be found in Figure 6 (right panel). Having these classifications, allows us to identify the treatment effect of the first lockdown for a milder (ring 1) and stronger exposure (ring 2) compared to objects that are supposed to be not extensively affected by air-traffic related noise. The results can be found in Table 6.

Table 6: Heterogeneity Effect – Noise Level

Dependent Variable:	log(flat price)
1^{st} Lockdown × Ring 2_{high}	0.044^{***}
	(0.013)
1^{st} Lockdown × Ring 1_{low}	0.025^{***}
	(0.006)
Full set of controls	Yes
Fixed-effects	
Months	Yes
Grids	Yes
Fit statistics	
Observations	71,608
R^2	0.91246
Within R^2	0.80719
Heteroskedasticity-robust standard-errors in parentheses	
*Signif. Codes: ***p < 0.01, **p < 0.05, *p < 0.1*	

Note: Heterogeneity analysis assuming different noise intensities with *Ring 1* being an indicator for living in areas with a noise level of 55 to 59dB (low noise before the pandemic) and *Ring 2* identifies regions of noise levels above 60dB (high noise).
Source: Authors' table.

As expected, the effect is substantially larger for those apartments with the higher noise exposure (4.4%) in contrast to the effect of 2.5% for the lighter affected apartments. Both effects are highly significant at the 1% level. The distribution of the coefficients with a stronger effect for highly affected apartment is reasonable.

Heterogeneity Effect – Time intervals and noise levels

The last heterogeneity test focuses on the combination of the first two by intersecting the time and spatial dimensions. Thus, the effect of different time intervals of the pandemic and of different treatment intensities are studied. The results are depicted in Table 7.

Table 7: Heterogeneity Effect – Time intervals and noise levels

Dependent Variable:	log(flat price)
Apr-May 2020 × Ring 2_{high}	-0.057*
	(0.032)
Apr-May 2020 × Ring 1_{low}	0.002
	(0.014)
Jun-Sep 2020 × Ring 2_{high}	0.036**
	(0.018)
Jun-Sep 2020 × Ring 1_{low}	0.027***
	(0.009)
Oct-Dec 2020 × Ring 2_{high}	0.030
	(0.021)
Oct-Dec 2020 × Ring 1_{low}	0.005
	(0.010)
Jan-Mar 2021 × Ring 2_{high}	0.081***
	(0.023)
Jan-Mar 2021 × Ring 1_{low}	0.034***
	(0.012)
Apr-Jun 2021 × Ring 2_{high}	0.068***
	(0.018)
Apr-Jun 2021 × Ring 1_{low}	0.043***
	(0.010)
Full set of controls	Yes
Fixed-effects	
Months	Yes
Grids	Yes
Fit statistics	
Observations	71,608
R^2	0.91248
Within R^2	0.80724

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***p < 0.01, **p < 0.05, *p < 0.1*

Note: Baseline regression with interaction between time and spatial dimensions. Period variables indicating a specific time interval of the

pandemic and *Ring 1* and *Ring 2* reflect areas of low (above 55dB) and high (60dB) noise levels.
Source: Authors' table.

Basically, this setup combines the prior temporal and spatial heterogeneity analyses. This similarity is also reflected in the results. The results from the prior analyses are also reflected in these results. The effects get stronger for the later periods. Again, the locations with higher noise levels are affected stronger than those with lower exposure rates.

Robustness – Pre-trends

Our study uses a difference-in-difference like setting to identify the effect of noise reductions during the pandemic on apartment prices. It is crucial to assume in this kind of setting that the treated and control objects behave similarly prior to the event (here the first lockdown in March 2020) such that the effect can be attributed to the start of the event. There should be no (significant) effect prior to this leading to the conclusion that the event causes the difference between treated and non-treated.

Figure 8 already showed graphical evidence for this by plotting the development of prices over time. To underpin the explorative analysis, we conduct to pretend analyses. First, we restrict our sample to the pre-lockdown period, i.e., our new observation period ranges from January 2018 to February 2020. The original lockdown is then shifted and we assume it was enacted in March 2019 – one year before the actual lockdown. The expected result would be that the interaction with the *NoiseContour* variables shows no significant effect and thus, supporting the argument that the actual lockdown drives the results. The regression output can be found in Table 8 column (1).

To intensify this argumentation even more, we split the pre-lockdown period into two-time intervals – January 2018 to January 2019 (labelled as *t-2*) and February 2019 to February 2020 (labelled as *t-1*). The treatment period is left unchanged and is set to the months after the lockdown (April 2020 to June 2021). March 2020, the month the implementation of the lockdown, functions as reference period in this setting. Again, the expectation is that pre-Corona periods show no significant effects when interacted with the *NoiseContour* dummy but the post-period indicator reports an effect. The results are shown in Table 8 column (2).

The placebo test gives no hint that the diff-in-diff setup is plagued by pre-trends of the treatment (or control) group. In the pre-treatment periods (t-1 and t-2) there are no significant effects found in the estimations. The coefficient for the implemented placebo lockdown also remains insignificant.

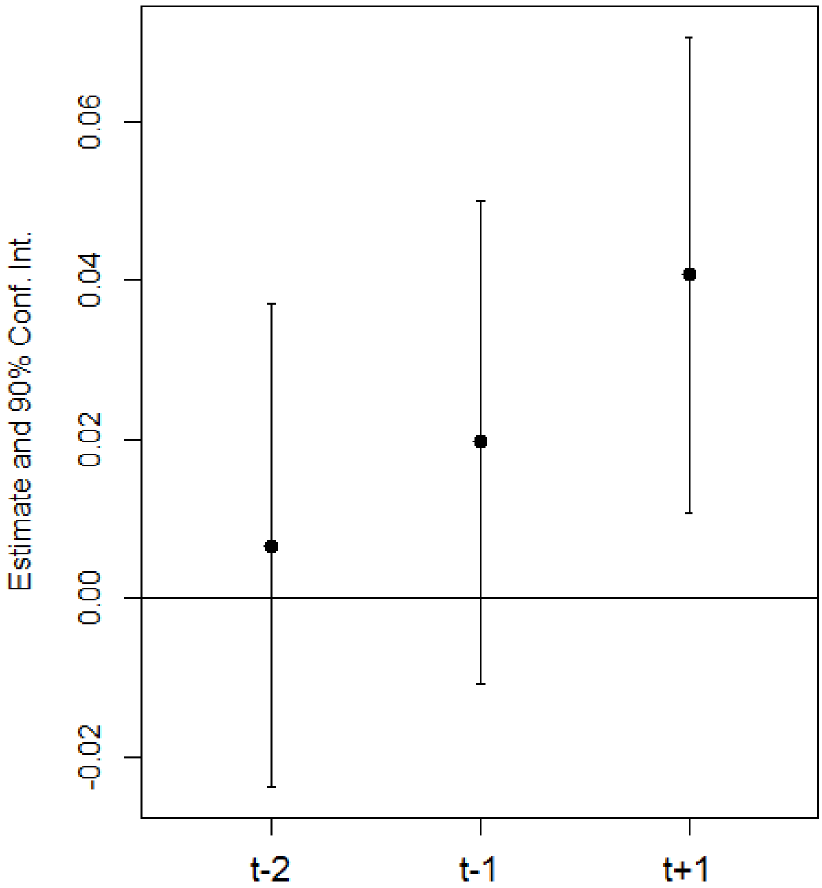
Table 8: Pre-trend results

Dependent Variable:	log(flat price)	
	(1)	(2)
Placebo lockdown × NoiseContour	-0.003	
	(0.007)	
Period_{t+1} × NoiseContour		0.041^{**}
		(0.018)
Period_{t-1} × NoiseContour		0.020
		(0.018)
Period_{t-2} × NoiseContour		0.007
		(0.018)
Full set of controls	Yes	Yes
Fixed-effects		
Months	Yes	Yes
Grids	Yes	Yes
Fit statistics		
Observations	41,222	73,214
R^2	0.91439	0.91262
Within R^2	0.80383	0.80724

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$*

Note: Column (1) shows the results for assuming a placebo lockdown in March 2019 (one year before the actual lockdown). Column (2) divides the pre-lockdown period into two intervals (*t-2*: January 2018-January 2019, *t-1*: February 2019-February 2020). The post-lockdown period is unchanged and March 2020 refers to the reference period (= *t*). *NoiseContour* indicates treated objects.
Source: Authors' table.

Figure 9: Effect size over time



Note: Graphical representation of the regression output shown in Table 8 column (2). Point estimates (dots) and their 90% confidence intervals (vertical lines) of the pre-trend analysis. *t-2* represents months between January 2018 to January 2019 and *t-1* months between February 2019 and February 2020. *t+1* is the post-lockdown period (April 2020 to June 2021). March 2020 functions as reference period (= *t*).
Source: Authors' graph.

Robustness – Leave-one-out-Estimation

To test the robustness of our baseline result, we conduct a leave-one-out estimation such that each of the nine airports is dropped from the sample once. Otherwise, the baseline setting is unchanged, i.e., the variable of interest is the interaction between the first lockdown in Germany (March 2020) and the indicator variable for being resident within the noise contour of a major airport.

Table 9: Leave-one-out estimation

Dependent Variable:	log(flat price)								
	(w/o DUS)	(w/o FRA)	(w/o HAM)	(w/o HAJ)	(w/o LEJ)	(w/o MUC)	(w/o STR)	(w/o CGN)	(w/o NUE)
1^{st} Lockdown × NoiseContour	0.028***	0.009	0.033***	0.032***	0.026***	0.027***	0.034***	0.030***	0.024***
	(0.006)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Full set of controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects									
Months	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Grids	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	62,439	53,010	57,388	69,084	69,093	69,572	64,866	63,478	63,934
R^2	0.91208	0.90959	0.91234	0.91153	0.90684	0.91253	0.91429	0.91567	0.91641
Within R^2	0.80180	0.80884	0.80836	0.80885	0.80880	0.80647	0.80527	0.81229	0.80766

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***p < 0.01, **p < 0.05, *p < 0.1*

Note: Repeated baseline regression with one airport left out at the time where Duesseldorf (DUS) is excluded in column (1), Frankfurt (FRA) in column (2), Hamburg (HAM) in column (3), Hannover in column (4), Leipzig (LEJ) in column (5), Munich (MUC) in column (6), Stuttgart (STR) in column (7), Cologne (CGN) in column (8), and Nuremberg (NUE) in column (9). *1^{st} Lockdown* indicates periods after March 2020 and *NoiseContour* determines treated objects within the noise contour.
Source: Authors' table.

Basically, the lockdown effect remains unchanged. In most cases, the effect varies between 2.4% and 3.4%. Only Frankfurt airport has a significant impact on the overall results. Once, Frankfurt is not implemented in the regression, the effect turns out to be insignificant.

Robustness – Including 1km buffer

A neutral zone was defined in all of the previous analyses. Control apartments that are located within one kilometer around the noise contour were excluded. The intention was to establish a clear cut between the treatment and control group without including objects in the control group that might be partially treated due to their mere close proximity to the noise contour. Otherwise, the treatment effect would be diluted and is expected to be smaller than with the exclusion of the neutral zone. To test this hypothesis, we reverse the previous setting and include the neutral zones in this last robustness check. The baseline regression is then repeated. The results are shown in following table.

Table 10: Including a 1km buffer

Dependent Variables:	log(flat price)
1^{st} Lockdown × NoiseContour	0.020***
	(0.005)
Full set of controls	Yes
Fixed-effects	
Months	Yes
Grids	Yes
Fit statistics	
Observations	85,593
R^2	0.91043
Within R^2	0.80627

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***p < 0.01, **p < 0.05, *p < 0.1*

Note: Repeated baseline regression with the inclusion of observations within a one-kilometer buffer around the noise contour. *1st Lockdown* indicates periods after March 2020 and *NoiseContour* reflects treated objects within the noise contour.
Source: Authors' table.

5. Conclusion

Identifying the effect of airport noise is a difficult task to undertake. Airports are large infrastructure projects which are publicly known long before their construction is completed. This evokes the issue of announcement effects. To bypass this challenge, we exploit the first Covid lockdown in March 2020 in Germany as source of variation in air traffic and aircraft-related noise. Due to travel bans and closed borders, the aviation sector took a hard hit leading to a strong decline in flight activity. We use this change and evaluate aircraft noise by applying a two-way fixed effects model.

The study builds on a granular data set which takes precisely geographically located apartments and connects them to noise contour maps of German airports. We also control directly for an extensive list of covariates such that the noise effect can be identified.

We are able to show a positive effect on apartment prices once the unexpected event of silence took place. Therefore, our study also contributes to the literature in the way that we show an absence of disamenities can improve living standards.

The baseline results suggest a price increase of around 3% after the lockdown was in place. The heterogeneity analysis reveals an even larger effect for later stages of the pandemic in 2021 (around 5%) and for those objects that are affected by higher noise levels before the pandemic (approximately 8%). 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. Especially, the pre-trend analysis, which identifies no significant effect in pre-Covid times, support our results and the hypothesis that the pandemic improved prices of close by apartments due to its effect on aircraft noise.

Conflict of Interest

The authors declare that they have no conflict of interest.

References

Ahlfeldt, G. M. and Maennig, W. (2010). Substitutability and Complementarity of Urban Amenities: External Effects of Built Heritage in Berlin. *Real Estate Economics*, 38(2):285-323.

Ahlfeldt, G. M. and Maennig, W. (2015). Homevoters vs. Leasevoters: A Spatial Analysis of Airport Effects. *Journal of Urban Economics*, 87, 85-99.

Baranzini, A. and Ramirez, J. V. (2005). Paying for Quietness: The Impact of Noise on Geneva Rents. *Urban Studies*, 42(4):633-646.

Boes, S., & Nüesch, S. (2011). Quasi-Experimental Evidence on the Effect of Aircraft Noise on Apartment Rents. *Journal of Urban Economics*, 69(2), 196-204.

Boes, S., Nüesch, S., & Stillman, S. (2013). Aircraft Noise, Health, and Residential Sorting: Evidence from Two Quasi-Experiments. *Health Economics*, 22(9), 1037-1051.

Breidenbach, P. (2015), Ready for Take-off? The Economic Effects of Regional Airport Expansion. *Ruhr Economic Papers #549*. RUB, RWI. DOI: 10.4419/86788627.

Breidenbach, P. & Eilers, L. (2018). RWI-GEO-Grid: Socio-economic Data on Grid Level. *Jahrbücher für Nationalökonomie und Statistik*. 238(6): 609-616. https://www.degruyter.com/document/doi/10.1515/jbnst-2017-0171/html.

Brueckner, J. K. (2003). Airline Traffic and Urban Economic Development. *Urban Studies*, 40(8):1455-1469.

Center for Disease Control and Prevention. (2019). What Noises Cause Hearing Loss? https://www.cdc.gov/nceh/hearing loss/what noises cause hearing loss.html. [Accessed: February 2022].

Cohen, J. P. and Coughlin, C. C. (2008). Spatial Hedonic Models of Airport Noise, Proximity, and Housing Prices. *Journal of Regional Science*, 48(5):859–878.

Cohen, J. P. and Coughlin, C. C. (2009). Changing Noise Levels and Housing Prices Near the Atlanta Airport. *Growth and Change*, 40(2):287–313.

Einig, K. (2015). Gewährleisten Zentrale-Orte-Konzepte gleichwertige Lebensverhältnisse bei der Daseinsversorge? *Informationen zur Raumentwicklung*, 1, 45-56.

Espey, M. and Lopez, H. (2000). The Impact of Airport Noise and Proximity on Residential Property Values. *Growth and Change*, 31(3):408-419.

Federal Environmental Agency. (2018). Basisdaten der Haupteisenbahnstrecken zur strategischen Lärmkartierung. https://www.govdata.de/web/guest/suchen/-/details/basisdaten-der-haupteisenbahnstrecken-zur-strategischen-larmkartierung-entsprechend-der-eu-umge. [Accessed: December 2021].

Federal Environmental Agency. (2019a). Lärmbelastung (Lden) in der Umgebung von Großflughäfen. https://www.govdata.de/daten/-/details/larmbelastung-lden-in-der-umgebung-vongrossflughafen-zur-strategischen-larmkartierung-entsprec. [Accessed: December 2021].

Federal Environmental Agency. (2019b). Lärmbelastung (Lden) in der Umgebung von Industrieanlagen in Ballungsräumen. https://www.govdata.de/web/guest/suchen/-/details/larmbelastung-lden-in-der-umgebung-von-industrieanlagen-in-ballungsraumenentsprechend-der-eu-u. [Accessed: December 2021].

Federal Environmental Agency. (2021). Weltweit: Flughäfen. https://www.govdata.de/web/guest/suchen/-/details/weltweit-flughafen. [Accessed: December 2021].

Federal Office for Building and Planning. (2020). Indikatoren und Karten zur Raum- und Stadtentwicklung – INKAR. Zentralörtlicher Status (zusammengefasst). https://www.inkar.de/. [Accessed: December 2021].

Federal Office of Statistics (FOS). (2022). Verkehr – Luftverkehr Dezember 2021. Fachserie 8. Reihe 6. https://www.statistischebibliothek.de/mir/receive/DESerie_mods_00000095.

Friedrich, J., Dietrich, P., & Furkert, M. (2021). Zentrale Orte in Deutschland. BBSR-Analysen Kompakt, 11/2021. https://www.bbsr.bund.de/BBSR/DE/veroeffentlichungen/analysen-kompakt/2021/ak-11-2021-dl.pdf?__blob=publicationFile&v=4. [Accessed: February 2022].

Jud, G. D. and Winkler, D. T. (2006). The Announcement Effect of an Airport Expansion on Housing Prices. *The Journal of Real Estate Finance and Economics*, 33(2):91-103.

Lawton, R. N., & Fujiwara, D. (2016). Living with Aircraft Noise: Airport Proximity, Aviation Noise and Subjective Wellbeing in England. Transportation *Research Part D: Transport and Environment*, 42, 104-118.

Lipscomb, C. (2003). Small Cities Matter, Too: The Impacts of an Airport and Local Infrastructure on Housing Prices in a Small Urban City. *Review of Urban & Regional Development Studies*, 15(3), 255-273.

McMillen, D. P. (2004). Airport Expansions and Property Values: The Case of Chicago O'Hare Airport. *Journal of Urban Economics*, 55(3), 627-640.

Milbert, A., & Furkert, M. (2020). Überversorgte Städte, Unterversorgtes Land? Regionale Selektionsprozesse im Bereich der Daseinsvorsorge. *Politikum: Analysen, Kontroversen, Bildung*, 6(3), 26-33.

Nelson, J. P. (2004). Meta-Analysis of Airport Noise and Hedonic Property Values. *Journal of Transport Economics and Policy*, 38(1):1-27.

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, *82*(1), 34–55.

RWI – Leibniz Institute for Economic Research. (2021a). RWI-GEO-GRID: Socioeconomic Data on Grid Level (Wave 11). https://doi.org/10.7807/microm:v11.

RWI – Leibniz Institute for Economic Research (2021c). RWI-GEO-RED: RWI Real Estate Data – Apartments for Sale. https://doi.org/10.7807/immo:red:wk:v5.1.

Schaffner, S. (2020). FDZ Data description: Real-Estate Data for Germany (RWI-GEO-RED) - Advertisements on the Internet Platform ImmobilienScout24. RWI Projektberichte, Essen.

Schlenker, W., & Walker, W. R. (2016). Airports, Air Pollution, and Contemporaneous Health. *The Review of Economic Studies*, 83(2), 768-809.

Tomkins, J., Topham, N., Twomey, J. and Ward, R. (1998). Noise versus Access: The Impact of an Airport in an Urban Property Market. *Urban Studies*, 35(2):243-258.6.

Winke, T. (2017). The Impact of Aircraft Noise on Apartment Prices: A Difference-in-Difference Hedonic Approach for Frankfurt, Germany. *Journal of Economic Geography*, 17, 1283-1300.