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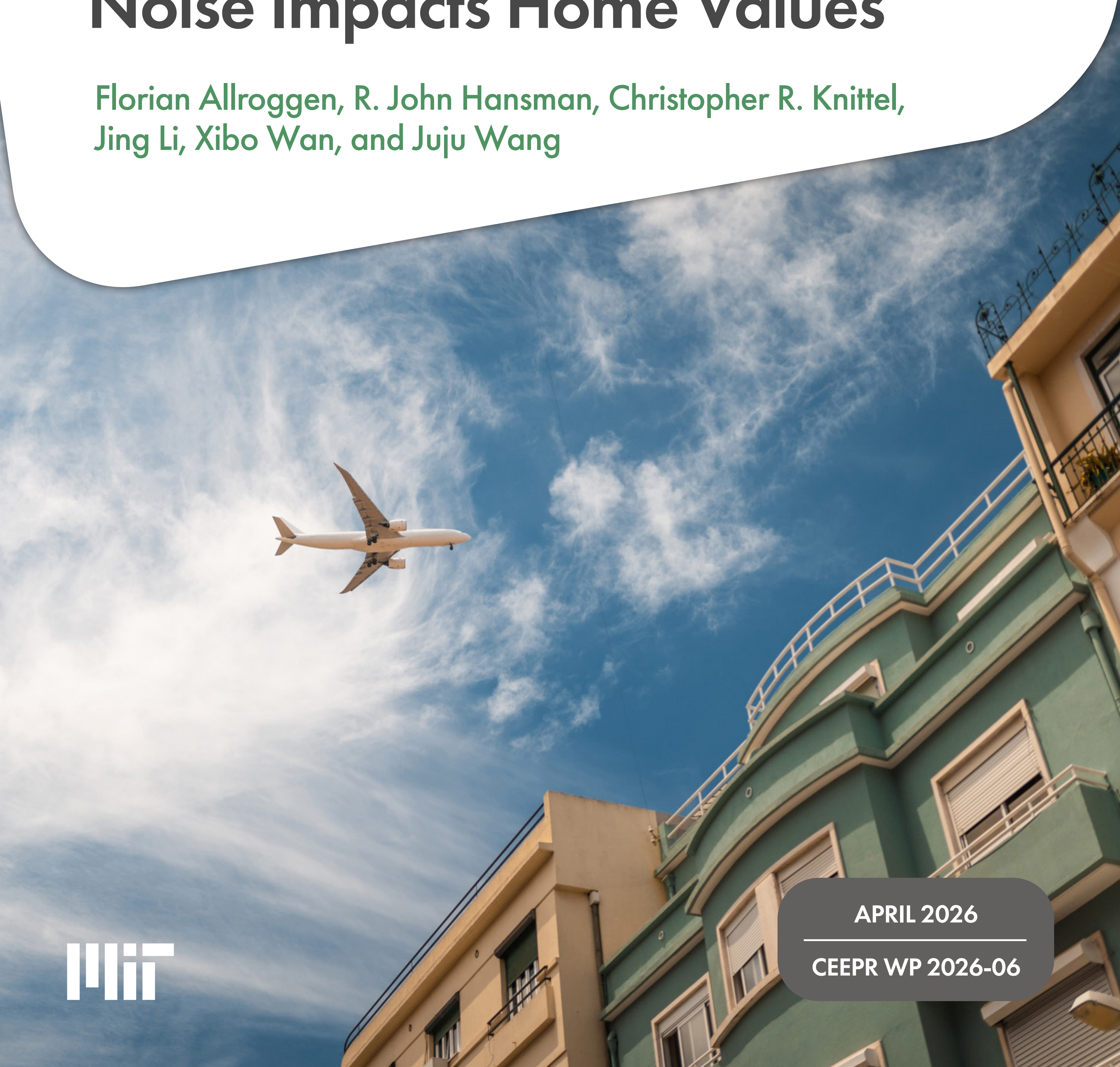

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Planes Overhead: How Airplane Noise Impacts Home Values

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Abstract

Air transportation supports economic growth and global connectivity but imposes localized environmental costs, particularly through aircraft noise. We estimate the causal effect of aviation noise on housing prices using quasi-experimental variation from the Federal Aviation Administration's rollout of performance-based navigation (PBN) procedures and runway reconfigurations at three major U.S. airports. Combining high-resolution flight trajectory data with geocoded housing transactions, we apply a difference-in-differences hedonic framework to identify changes in exposure unanticipated by residents. A one-decibel increase in annual day-night average sound level reduces house prices by 0.6 to 1.0 percent. Among alternative noise metrics, average exposure explains property value impacts most strongly. Willingness to pay for quieter conditions varies systematically with income and race, indicating that aircraft noise externalities have meaningful distributional consequences. Our results highlight the need to incorporate localized environmental costs into aviation and urban land-use policy.

Keywords: aircraft noise exposure; hedonic price model; quasi-experiment
JEL Codes: D81, I38, L51, L65

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1 Introduction

Air transportation plays a critical role in modern economies by facilitating trade, tourism, and connectivity between cities and regions (Allroggen and Malina, 2014; Button and Yuan, 2013; Percoco, 2010). Through these channels, air travel fosters productivity growth and regional development. At the same time, air transportation is a significant source of environmental externalities, including greenhouse gas emissions, local air pollution, and noise. Aircraft operations generate both global impacts—such as climate change—and local ones, such as air quality deterioration (Grobler et al., 2019) and noise exposure (Nelson, 2004). Unlike other environmental effects, noise externalities are spatially concentrated around airports and directly affect nearby communities. Exposure to aircraft noise has been linked to annoyance (Ragettli et al., 2016), sleep disturbance (Hume et al., 2012), and adverse cardiovascular and respiratory outcomes (Grampella et al., 2017). These localized effects can influence neighborhood desirability and, consequently, housing market outcomes.

This paper examines the causal effect of aircraft noise exposure on residential real estate transaction prices ("house prices") in the United States. Specifically, we estimate how quasi-random changes in airplane noise exposure affect housing values in neighborhoods surrounding major airports. Identifying the causal effect of noise is challenging because residential sorting and unobserved amenities often confound the relationship between noise exposure and housing prices. To address these concerns, we exploit exogenous changes in flight paths that alter local noise exposure in unanticipated ways. The resulting variation allows us to estimate the contemporaneous, capitalized effect of aircraft noise on property values.

Our identification strategy relies on two independent sources of plausibly exogenous variation. First, we leverage the nationwide implementation of the Federal Aviation Administration's (FAA) performance-based navigation (PBN) procedures beginning in 2006. PBN replaced conventional radar-based navigation with satellite-guided routing, enabling more precise and concentrated flight paths to and from airports. These changes altered aircraft trajectories—often without public anticipation or prior knowledge by affected residents—creating localized increases or decreases in noise exposure. Second, we exploit runway reconfigurations associated with airport capacity expansions, which change takeoff and landing patterns independently of neighborhood characteristics (El-Fadel et al., 2002). Together, these sources of variation provide a rich quasi-experimental setting to identify the effect of airplane noise on housing prices while mitigating omitted-variable bias due to endogenous residential location choices.[1]

Measuring the resulting changes in noise exposure requires high spatial and temporal resolution. We combine radar-based flight trajectory data from the Airport Surface Detection Equipment Model X (ASDE-X) system with detailed noise propagation modeling to create a high-resolution (0.25-nautical-mile) dataset of aircraft noise. This dataset captures actual, as-flown trajectories and aircraft-specific noise profiles, producing a precise measure of localized exposure intensity. We link these data to residential real estate transactions from 2011 to 2016 in neighborhoods within a 20-by-20 nautical mile area surrounding three major airports: Boston Logan International Airport, Chicago O'Hare International Airport, and Seattle-Tacoma International Airport. These three urban areas were selected because each experienced substantial flight path changes during our period of analysis, providing meaningful variation in exposure. In addition, we apply the flexible difference-in-differences hedonic model proposed by Banzhaf (2021) to mitigate potential conflation bias from shifts in hedonic gradients following environmental changes (Chay and Greenstone, 2005; Gayer et al., 2000; Black, 1999; Greenstone and Gallagher, 2008; Davis, 2011).

Our results indicate that homes experiencing a 1 percent increase in airplane noise exposure sell for 0.2 to 0.3 percent less than comparable homes without such changes. This corresponds to a Noise Depreciation Index (NDI) of approximately 0.6 to 1.0, implying that a 1-decibel increase in average noise exposure reduces property values by 0.6 to 1.0 percent. These estimates are consistent across the three cities and align closely with prior research (Nelson, 2004; He et al., 2014; Kopsch, 2016; Boes et al., 2013; Ossokina and Verweij, 2015; Tsui et al., 2017; Nguy et al., 2014). The magnitude of our estimates suggests that aircraft noise remains a significant disamenity for households, even in urban areas with long-standing exposure.

We also find considerable heterogeneity in the willingness to pay (WTP) for noise abatement, both across and within cities. On average, Boston residents are willing to pay \$152 per year for a one dBA reduction in average annual day-night sound level (DNL), with a median of \$126 and an interquartile range of \$97. In Chicago, the corresponding mean WTP is \$104 (IQR \$72), and in Seattle, it is \$221 (IQR \$168). Applying these values to assess the welfare implications of flight path changes, we find that reverting to the 2011 baseline would yield average WTP gains of \$432 per household in Boston and \$168 in Seattle, whereas Chicago households would require approximately \$122 in compensation to return to prior conditions. Within each city, heterogeneity in WTP correlates with income, racial composition, and the distribution of noise exposure changes,

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[1] See discussions in Rosen (1974); Parmeter and Pope (2013); Kuminoff et al. (2010); Parmeter et al. (2007).

suggesting important distributional implications for airport policy.

We conduct extensive robustness and sensitivity analyses to assess the stability of our estimates. Excluding high- and low-price outliers yields results nearly identical to the baseline. Expanding the sample window to include earlier and later years (pre-2011 and post-2016) produces similar coefficients, as do alternative functional forms such as Box-Cox and semi-log specifications. The log-log specification remains our preferred model because it provides a natural elasticity interpretation and consistent estimates across cities. These robustness checks confirm that our results are not driven by sample composition or model specification.

Our paper makes four main contributions to the literature.

First, we assess the impacts of aircraft noise on house prices using a comprehensive geospatial approach that extends far beyond conventional noise contour maps. Prior studies often focus on limited areas defined by FAA DNL thresholds, typically within 65-75 dBA contours. In contrast, we examine the full 20-by-20 nautical mile area around each airport, capturing a broader gradient of exposure changes (McMillen and McDonald, 2004; Pope, 2008; Boes and Nüesch, 2011a). By analyzing multiple urban areas, we also test the external validity of our findings across distinct real estate markets.

Second, we construct a high-resolution measure of aircraft noise exposure using ASDE-X radar flight trajectory data. This enables us to model noise at a spatial precision of 0.25 nautical miles, accounting for as-flown trajectories and aircraft type-specific noise profiles. Compared to prior studies relying on modeled DNL contours or averaged noise grids (Boes and Nüesch, 2011b; McMillen, 2004; Cohen and Coughlin, 2009), our data allow us to capture fine-scale heterogeneity in exposure intensity. This precision is critical for identifying localized noise effects on housing prices, especially where flight path concentration creates sharp intra-neighborhood variation.

Third, we examine multiple dimensions of noise exposure simultaneously. Whereas most of the literature relies on cumulative annual measures like DNL (McMillen and McDonald, 2004; Pope, 2008; Boes and Nüesch, 2011a), residents may respond differently to the average noise level, the frequency of events, or the variability in noise intensity. Building on Levesque (1994), we decompose aircraft noise into three components: average noise level, number of overflights, and distribution of peak events. We find that the average noise level explains most of the housing price response, suggesting that residents value persistent reductions in exposure more than reductions in occasional high-noise events.

Finally, our paper contributes to the hedonic valuation literature on non-marginal environmental changes (Bajari and Benkard, 2005; Bishop and Timmins, 2018; Von Graevenitz, 2018). We show that exogenous noise exposure changes induced by navigation technology adoption and runway reconfiguration can meaningfully alter the hedonic price function. By estimating the full demand function for aircraft noise exposure, we highlight substantial heterogeneity in preferences across demographic and income groups. These findings also contribute to the broader literature on airport externalities and environmental justice, linking physical exposure to economic outcomes (Schlenker and Walker, 2016; Dean, 2024).

The rest of the paper proceeds as follows. Section 2 describes the institutional background and the nature of flight path changes around the three airports. Section 3 details the data, including the construction of our high-resolution noise exposure measures and housing transaction dataset. Section 4 outlines our empirical methodology and identification approach, followed by Section 5, which presents the baseline estimates and robustness checks. Section 6 discusses the welfare implications of our results and examines heterogeneity in WTP across populations. Section 7 concludes.

2 Background and Study Area

2.1 Airports, Airplanes, and Noise Exposure

Air traffic to and from airports leads to noise exposure in communities surrounding airports. While the spatial distribution of such noise exposure depends on the exact operational details (e.g., prevailing winds, runway orientation, or aircraft), it tends to be highest closer to airports as aircraft fly at low altitudes during their climb and descent. Noise exposure has been linked to detrimental impacts on human health and economic outcomes, including annoyance, sleep deprivation, cardiovascular disease, productivity, and children's learning behavior (Dean (2024); Hegewald et al. (2020); Peters et al. (2018); Black et al. (2007)).

Revealed preferences in the housing market offer a way to understand how residents value quieter environments. Unlike stated preference methods, revealed preference studies use actual market behavior and study how property prices reflect noise exposure. Prior research shows that aircraft noise reduces housing values, with properties closer to airports or under flight paths selling for less than comparable homes in quieter areas (Nelson (2004); Theebe (2004); Boes and Nüesch (2011a)). Previous research provides some evidence that the extent of this discount varies based on noise intensity, community characteristics, and housing market conditions. Additionally, changes in airport operations or noise abatement policies can influence how noise is capitalized into housing prices (Friedt and Cohen (2021)).

Most studies about communities' aircraft noise exposure rely on aggregate, average noise exposure. However, the frequency and timing of aircraft operations can also affect local noise impacts, particularly in densely populated urban areas. For example, aircraft operations during nighttime hours could be particularly disruptive, as they might interfere with sleep and contribute to feelings of fatigue and irritability (Kwak et al. (2016); Stansfeld et al. (2010)).

Over the past two decades, flight paths for some US airports have changed significantly due to the implementation of Performance-based Navigation (PBN) procedures (Nakamura and Royce (2008); Eagan et al. (2013)). PBN uses advanced technologies to determine flight paths while taking into account a wide range of factors, including aircraft performance capabilities, weather conditions, terrain, and other obstacles. Through the use of technologies such as satellite-based Global Navigation Satellite Systems (GNSS), PBN enables more accurate navigation. This transition has changed flight paths, including during take-off and landing. Most importantly, it led to a concentration of flight trajectories and subsequently noise exposure.

Runway configurations also impact flight paths and, consequently, the communities affected by aircraft noise. For an airport with prevailing westerly winds, aircraft will typically take off to the west if a runway oriented east to west exists. Similarly, aircraft approaching such an airport will typically approach from the east. This means that neighborhoods east and west of the airport will likely be overflown by aircraft and will experience the associated noise exposure. That said, changes in runway configurations can result in variation of flight paths, thereby impacting the spatial distribution of noise exposure in nearby communities. Airports may open and close runways for various reasons, such as maintenance, weather conditions, operational efficiency, and noise reduction.

2.2 Study Area

We study the impact of airplane noise on nearby communities for three US airports: Boston Logan International Airport (BOS), Massachusetts; Chicago O'Hare International Airport (ORD), Illinois; and Seattle-Tacoma International Airport (SEA), Washington. We choose these locations due to the availability of detailed flight track data, as well as observed changes in flight paths due to the introduction of PBN procedures and changes to runway configurations.

Boston Logan International Airport (BOS) is an international airport in Boston, Massachusetts. It is the largest airport in New England. The airport is located about three miles from downtown Boston. Boston Logan has six runways with different orientations; thus, its operational pattern and associated community noise exposure can change between operating days, depending primarily on wind direction. Boston Logan Airport implemented its first set of Performance-based Navigation (PBN) procedures in 2014 for Runway 4R/22L. Additional PBN procedures were added in the following three years. Figures A1a and A1b show the changes in flight tracks from 2011 to 2016 in June. We observe a concentration of tracks across all major arrival and departure paths, as expected with PBN procedures.

Chicago O'Hare International Airport (ORD), located in the northwestern part of Chicago, has long faced infrastructure constraints which eventually drove the O'Hare Modernization Program (OMP)—a comprehensive effort to reconfigure intersecting runways into parallel alignments, aimed at increasing capacity and reducing delays (WSP, 2025). As part of this effort, Runway 10C/28C was commissioned in October 2013. Subsequently, Runway 14L/32R was permanently closed in 2015 to make room for improvements, and the new Runway 10R/28L opened in October 2015 (O'Hare Noise Compatibility Commission, 2025). A later phase saw Runway 14R/32L renamed to 15/33 in September 2016, with the runway eventually closed by March 2018.[2] Concurrently, the FAA began deploying Performance-Based Navigation (PBN) procedures starting in 2013 and scaled up implementation across all runways by 2016, part of a national strategy that nearly tripled available PBN procedures between 2009 and 2016 (U.S. Government Accountability Office, 2021).[3] These combined runway realignments and PBN enhancements reshaped traffic flows and, as shown in Figures A1c and A1d, increasingly routed flights over neighborhoods east and west of ORD.

Seattle-Tacoma International Airport (SEA) is located between Seattle and Tacoma in the State of Washington. It is the largest airport in the Pacific Northwest region. In 2012, Seattle-Tacoma Airport began implementing Performance-Based Navigation (PBN) procedures for its runways, starting with Runway 16C/34C. Additional PBN procedures were implemented for Runway 16L/34R in 2014 and Runway 16R/34L in 2015. The airport completed the implementation of PBN procedures for all of its runways in 2017. Figures A1e and A1f show changes in flight tracks from 2011 to 2016 at Seattle Tacoma Airport. Visually, the patterns and distributions exhibit little change, with only a moderate visible concentration of flight tracks.

At these airports, the adoption of PBN and changes in runway configuration provide a quasi-experimental setting to assess the contemporaneous relationship between airplane noise exposure and the housing market. Data on daily operating activity from observed flight tracks allow us to

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[2] `https://de.wikipedia.org/wiki/Flughafen_Chicago_O%27Hare#Start-_und_Landebahnen`

[3] `https://en.wikipedia.org/wiki/NextGen_(Federal_Aviation_Administration)`

understand noise exposure around airports at high spatial resolution. The data also provide a unique opportunity to distinguish the relative importance of different noise characteristics as represented by the average noise level, the intensity of extremely loud events, and the duration of these loud events as factors influencing residential property prices.

3 Data and Summary Statistics

The analysis presented in this paper builds upon comprehensive datasets for flight tracks and property values in counties surrounding the three US airports that we study. These data allow for fine-grained analysis of how local airplane noise impacts areas beneath the flight path in a 20x20 nautical miles geospace around the airports. The following subsections describe the various datasets in more detail.

3.1 Flight Track Data

To measure changes in local airplane noise, we use detailed flight track data from the Airport Surface Detection Equipment, Model X (ASDE-X)[4]. The dataset contains a series of time-stamped data points with latitude, longitude, altitude, and identifying flight numbers, which allow us to model flight paths for all flights. To estimate the airplane noise exposure in local communities, we generate a noise lookup table with Aviation Environmental Design Tool (AEDT) outputs (Roof et al., 2007), using various aircraft types and departure and approach pathways for each runway[5]. We then merge the noise power distance curves from AEDT onto our flight track data to obtain accurate contour data on a per-flight basis. Individual flight noise contours can then be aggregated to compute daily and annual exposure. This process enables the calculation of precise aircraft overflight noise data while accounting for differences in noise by aircraft type.

Our analysis focuses on 2011 and 2016 since most PBN procedures were implemented between 2011 and 2016. Our study expands the geographic coverage that is typically considered by the literature to encompass a 20x20 nautical mile radius around the airports.

Aircraft noise exposure can be quantified through several metrics that capture different exposure characteristics, such as duration, levels, and frequency of events. Under the Aviation Safety and Noise Abatement Act of 1979, the FAA adopted the day-night average sound level (DNL) as a

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[4] ASDE-X is a tool that helps air traffic control monitor aircraft and vehicles at airports.

[5] AEDT is a software tool used to evaluate the environmental impact of aviation operations, such as airplane noise and emissions.

regulatory metric. DNL is a measure of average noise exposure over the course of a day, considering all aircraft operations that occur:

$$DNL = 10 * log\frac{1}{24}(\sum_{day} 10^{\frac{L_{day}}{10}} + \sum_{night} 10^{\frac{L_{night}+10}{10}}) \tag{1}$$

where L_{day} is the energy-equivalent sound level of noise events during the daytime and L_{night} is the energy-equivalent sound level of noise events during the nighttime. The metric uses frequency weights (A-weighting) to adjust for how humans perceive sound, and units are in dBA (A-weighted decibels). Events at night (after 10:00 p.m. and before 7:00 a.m.) are penalized by 10 dBA to account for the increased disturbance of noise during the night hours.

While DNL is a metric of average exposure levels, other metrics might be better suited to capture different noise characteristics. For example, residents might be sensitive to the intensity and duration of "loud" events at a location. To better capture such potential sensitivities, we introduce two additional noise metrics: the number of events in a location exceeding a specified level on a "peak day" (i.e., the day with the highest DNL in a year), as well as the percentage of days where a threshold is exceeded more than 40 times. Following Jensen et al. (2017), we use 60 dBA as an indicator of substantial noise events. Taken together, these metrics represent intra-day frequency and likelihood of days with substantial exposure.[6]

Insert Figure 1 Here

Figures 1a-1c plot the spatial distribution of DNL changes from 2011 to 2016 for residential properties in our sample. Increases in noise exposure are concentrated along major flight paths to and from each of the airports. The DNL change in Boston area homes ranges between -2 and 11 dBA, where the most substantial increases are concentrated in areas under the 33L runway departure flight path and in narrow corridors along the flight tracks. Over our study period, houses in the Boston sample experienced an average increase of 2.3 dBA in DNL. In Chicago, the change in noise exposure ranges between -10 and 6 dBA, with higher exposure in the East and West areas but lower noise exposure in the Northeast, Southeast, Southwest, and Northwest. These large-scale changes are likely associated with changes in runway configuration in Section 2.2. The houses in the Chicago sample experienced an average decrease of 1.1 in DNL from 2011 to 2016. The variation in

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[6] We test the sensitivity of our results using alternative cutoffs for both the definition of a loud event and the number of events.

noise levels in Seattle varies between -2 and +3 dBA. This more homogeneous change is the result of no runway configuration changes and runways oriented in the north-south direction, which leads to flight paths that change relatively little over time.

3.2 Housing Transaction Data

We collect transaction-level housing prices and characteristic data in the three urban areas during the 2011-2016 period from the Zillow Transactions and Assessment Dataset (ZTRAX) (See Table 1) for descriptive statistics). Zillow aggregates these data from several sources, including county assessor offices.[7] All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. We clean the transaction data in several ways. First, we follow Currie et al. (2015) and restrict our sample to homes that sold for above $50,000 but below $2 million. This filter helps remove the effect of outliers.[8] Second, we restrict the sample to single-family and multi-family homes in line with the purpose of our study. Third, we restrict our sample to arms-length transactions by ruling out intra-family transactions and transactions with unfair market prices (e.g., property sold under financial distress or including extra incentives). Fourth, we drop properties that sell more than once within a calendar year. Fifth, we exclude houses with incorrect or missing geolocations. Finally, we drop observations that are likely erroneous or outliers, such as listings of houses built more than five years after being sold, with square footage greater than 20,000, with a number of bedrooms or bathrooms greater than six, or with a number of stories greater than three. We also impute the missing value of the number of stories and bedrooms using total living area information in our samples.[9]

We focus on housing data in 2011 and 2016 to examine how the change in airplane noise affects local housing prices in our three localities. We test the robustness of our results by extending our data to multiple years before 2011 and after 2016, with the assumption that there are no significant noise changes over these time periods. The Boston sample covers residential real estate transactions in five counties (Suffolk, Norfolk, Plymouth, Middlesex, and Essex) with 21,989 housing

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[7] Data are provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.

[8] Many studies followed a similar strategy by eliminating very high-priced (above the 99th percentile) and low-priced (below the 1st percentile) homes to remove outliers on our econometric results. See similar discussion in Bishop and Timmins (2018).

[9] We manually check the geographic datum of selected houses by matching the Assessor parcel number between the transaction data and state parcel maps, most of them towards NAD83/WGS84. See more detailed discussion in Nolte et al. (2021).

transactions. The Chicago sample includes two counties (Cook and DuPage) and consists of 33,913 housing transactions. The Seattle sample includes one county with 30,136 transactions.[10] We geocode the sales records and merge the sales records with shapefiles of house locations, house characteristics, and the georeferenced airplane noise data. All addresses within a noise grid of 20-by-20 nautical miles around each airport are considered. Each house is assigned a continuous measure of nearest noise exposure based on its location.[11]

Changes in housing prices over our study period are shown in Figure 1d-1f. From 2007-2011 to 2016-2020, housing prices in Boston varied across different neighborhoods. In more central locations, for example, the average price of housing increased significantly over this period of time, while in other areas, we observe a decrease in average house prices. For communities close to Chicago O'Hare airport, communities in the eastern and northeast areas saw increases in average housing prices during this time period, while communities in other areas experienced a small decline. Finally, housing prices in the northern area of Seattle experienced increases, while for houses in the southern area, the average housing price remained nearly the same.

Figure 1g-1i shows the correlation between housing price changes and DNL changes across the three localities. The correlation coefficient in Boston is 0.195 ($p < 0.01$), suggesting that house prices increased in areas where noise exposure increased. While counterintuitive at first sight, this could be driven by the close proximity of the airport to inner-city areas. We find an almost zero correlation (0.001, $p > 0.1$) in the Chicago sample and a negative correlation (-0.206, $p < 0.01$) in the Seattle sample. We expect that numerous confounding factors influence housing prices, so this correlation analysis cannot provide detailed insights into the causal relationship between aircraft noise exposure and housing prices. Such confounding variables may include characteristics of residential properties, such as the number of bedrooms and bathrooms, and lot size. Table 1 provides descriptive statistics for the collected data.

3.3 Other Demographics and Amenity Data

We collect data to serve as control variables from a variety of sources. To control for demographic differences, we include: the median household income, the percentage of people under 18 years of age, and the percentage of the non-white population. These are collected from the Census TIGER/Line Database with Selected Demographic and Economic Variables. To capture neighborhood effects,

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[10] Appendix Table A2 shows more details about how the housing characteristics evolved as we put more restrictions on our data.

[11] See more details of how we match houses with noise grid in Online Appendix A.2.

we also calculate the distance from each property to the main (dis)amenities, such as the city hall, road, rail, coastline, open spaces, and shopping malls. The major city point locations are collected from ArcGIS Hub.[12] Road and rail shapefile are obtained from Census data. Shopping mall and open space data are collected from MyGeodata Cloud.[13] Since the benefits or losses associated with local (dis)amenities can be assumed to dissipate with distance, we calculate the linear distance from each house to the nearest location and use a spatial decay function as shown in equation (2) to relate houses to benefits from local (dis)amenities:

$$Dist_{ik} = max[1 - (\frac{d_{ik}}{d_{max}})^{\frac{1}{2}}, 0], \tag{2}$$

where k denotes the amenity; d_k denotes the distance to the amenity in meters; and d_{max} is a cutoff point set to 500 meters for our application.[14] This function creates a convex index between 0 and 1.

Insert Table 1 Here

3.4 Descriptive analysis of house and neighborhood characteristics

Table 1 reports descriptive data on house characteristics and neighborhood attributes across the three localities.

For the Boston area, in 2011, the average house sold for approximately \$447k. By 2016, the price increased to \$553k. Over this same period, the average annual DNL rose from 42.96 dBA to 46.33 dBA. The average house was 79 years old, with four bedrooms, two baths, and 2,286 square feet of living area on a 9,303 square feet lot. It was located in a block group where 22% of the neighborhood was nonwhite, 20% was under 18 years of age, and had an average of \$85,650 median family income. Most houses are within a 500-meter radius of the city hall, given the small city structure of the Boston area, while only a few houses are close to the shopping malls and coastal lines.

The average properties in the Chicago sample had an approximately 13 percent increase in house prices, were exposed to about 1 dBA lower airplane noise levels, were 58 years old, had three bedrooms, two baths, and a 7,844 square feet lot. They were located in a block group where 24%

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[12] https://hub.arcgis.com/datasets/esri::usa-major-cities/explore?location=27.973546%2C-113.479736%2C3.82

[13] https://mygeodata.cloud/

[14] Phaneuf et al. (2008) uses the same cutoff for the distance to the lake amenity. We test alternative cutoffs for each amenity and find robust results across specifications.

of the neighborhood was nonwhite, 22% was under 18 years of age, and had an average of $82,690 median family income. There is a comparatively low density of houses close to city halls, shopping malls, and open spaces, relative to the Boston sample.

The average home in the Seattle sample had a 28 percent increase in house prices, was exposed to 1.2 dBA higher airplane noise levels, was 34 years old, had three bedrooms, two baths, and an 11,961 square feet lot. They were located in a block group where 34% of the neighborhood was nonwhite, 20% was under 18 years of age, and had an average of $76,240 median family income. Like Chicago, there is a relatively low density of houses close to city halls, shopping malls, and open spaces, as compared to the Boston sample.

4 Empirical Strategy

Changes in flight paths due to new runways or adopting PBN procedures offer an opportunity to study the causal effects of noise exposure on housing prices in a quasi-experimental setting. We argue that changes in noise levels within a particular, localized geographic area can be considered exogenous over our study period for the following reasons. First, the requirements of the PBN procedure determine the changes in flight paths and altitudes, which are developed and implemented by the Federal Aviation Administration (FAA). These requirements are based on factors such as safety, airspace capacity, and efficiency (Timar et al., 2017). Second, the decision to open or close a runway is most likely based on operational efficiency, available space, weather conditions, maintenance needs, or safety considerations.

To identify the capitalization effects of airplane noise on housing prices, we employ a hedonic difference-in-differences (DD) design. The key source of variation is the spatial and temporal variation in aircraft noise exposure changes around airports over our study period. Most importantly, such variation includes noise exposure changes associated with the implementation of PBN procedures or changes in runway configuration as discussed above. We estimate the average treatment effect of noise exposure changes using the following specification:

$$lnP_{ijt} = \beta_0 + \beta_1 lnDNL_{ijt} + \beta_2 Z_{ijt} + \gamma_{jy} + \eta_m + \epsilon_{ijt}, \tag{3}$$

The outcome of interest is lnP_{ijt}, the log of the sale price for property i at geographic unit j in date t; $lnDNL_{ijt}$ is the log of noise exposure (measured as DNL) of property i at geographic unit j in date t; Z_{ijt} is a vector including house characteristics (property age, building area, and house condition, etc.), neighborhood attributes (block-group level household median income, the percentage of people under 18, and the percentage of the non-white population), and distance index to local (dis)amenities (city hall, rail, road, coastal line, shopping mall, and open space).[15] γ_{jy} is the spatial fixed effects, which is discussed in more detail below. We further include month fixed effects η_m for each month m to control for the seasonality of housing prices. ϵ_{ijt} is an idiosyncratic error term. We estimate the equation separately for each of the three real estate markets, and all regressions use Eicker-White standard errors. The coefficient of interest is β_1, the estimated impact of airplane noise on housing prices. It measures the percentage change in the average house price due to a one percent change in noise exposure. To make our estimates more comparable to previous studies on noise impacts, we use the average annual noise levels in 2011 and transform the coefficient for DNL in the log-log model to the noise depreciation index (NDI), which refers to the percentage change in price for one dBA change in average noise levels. We explore the sensitivity of our results by using alternative time windows for pre- and post-period, alternative housing sale price bounds, alternative spatial fixed effects, and alternative function forms.

We make three additional sets of assumptions in our empirical model. First, we consider three sets of spatial fixed effects at the zip-code level, the census-tract level, and a 2x2-mile-grid level. Such fixed effects allow us to control for average time-invariant characteristics, including time-invariant noise levels. The choice of spatial resolution for such fixed effects is subject to trade-offs: On the one hand, we prefer a high spatial resolution of fixed effects to control for unobserved characteristics and avoid endogenous noise variation to enter the analysis. However, such high-resolution fixed effects would soak up the local impacts of noise exposure, leaving little to no variation to estimate β_1.[16] Figure A6 shows the scale of three resolutions of the fixed effects and the associated DNL changes within each region over our study period in the three localities of interest. The average size of the zip code in the Boston sample is around 12 square miles, varying from 1.5 to 57 square miles. Chicago has a similar average size of 12 square miles, while the average size in Seattle is around 32 square miles. These differences are likely due to the lower population density in the Seattle area[17]. The average size of census tracts in Boston and Chicago is around 2.6 square miles, while the average size in Seattle is 5 square miles. Similar trends are visible for census tracts, with average

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[15] Airplanes also generate air pollution and there is a well-established cause relationship between air pollution and home values (Grineski et al. (2007); Nourse (1967); Pratt et al. (2015); Chay and Greenstone (2005); Bayer et al. (2009)). However, the air pollution generated by aircraft will likely disperse more readily than noise pollution.

[16] Banzhaf (2021) suggests using zip codes or census tracts as geographic units for spatial fixed effects might further be problematic if small geographies are systematically more homogeneous than large ones and if large geographies also vary systematically in unobserved ways from other areas. Banzhaf (2021) proposes that arbitrary zones like a 2-mile grid are preferable to census geographies when controlling for spatial effects.

[17] https://www.city-data.com/compare/Seattle-WA-vs-Boston-MA?

size ranging from 2.6 square miles in Boston and Chicago to 5 square miles in Seattle. As shown in Figure A6, little variation in airplane noise remains within the relatively small census tracts in Boston and Chicago after controlling for census-tract or grid-level fixed effects. We subsequently chose zip code fixed effects for the Boston and Chicago samples while using census tract fixed effects for the Seattle sample.

Second, the gradient of the hedonic price function might shift due to exogenous changes in airplane noise. For example, if overall noise levels increase across the region due to higher air traffic, households may re-optimize their location choices, altering the implicit prices of both noise exposure and correlated housing attributes. In this case, the gradient of the hedonic price function would adjust to clear the housing market, and the estimated capitalization effect may no longer represent the true willingness to pay (WTP) for noise reduction. Instead, it conflates two components: (i) households' valuation of the change in airplane noise itself and (ii) shifts in the shadow prices of noise and related amenities that arise from broader market adjustments. This conflation bias implies that the average capitalization effect can diverge from the average household's marginal WTP. To test this conflation bias, we follow Banzhaf (2021) and allow the hedonic coefficients to evolve between the two time periods by interacting the pre- and post-period dummies with noise measures and house attributes. This permits the capitalization effect to identify marginal willingness-to-pay (MWTP) in the post-shock equilibrium, conditional on the assumption that the changes in noise exposure are orthogonal to the initial level of the house and neighborhood characteristics and to changes in these variables.[18] This specification is as follows:

$$lnP_{ijt} = \beta_0 + \beta_{11} lnDNL_{ijt,pre} + \beta_{12} Z_{ijt,pre} + \beta_{21} lnDNL_{ijt,post} + \beta_{22} Z_{ijt,post} + \gamma_{jt} + \eta_m + \epsilon_{ijt}, \quad (4)$$

where $lnDNL_{ijt,pre}$ is the interaction between the log of noise measures and pre-period indicator; $Z_{ijt,pre}$ is the interaction between house attributes and pre-period indicator. Similarly, $lnDNL_{ijt,post}$ and $Z_{ijt,post}$ are the interactions between the post-period indicator and noise and house attributes, respectively. The remaining variables are the same as in equation 3.

Finally, we explore the effects of noise attributes other than average noise levels on house prices. In particular, we study the impacts of the frequency of loud events and of the variability of loud events occurring over the year.[19] To separate the effect of average noise level from the impacts of the

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[18] Banzhaf (2021) and Kuminoff et al. (2010) have a detailed discussion about how the shift would affect the interpretation of welfare measures.

[19] We define the frequency of loud events as the number of noise events above 60 dBA on a peak day, and define the variability of exposure to loud events over the year as the percentage of days with more than 40/50/60 noise events

frequency of loud events and from the variability in daily exposure to loud noise events, we include different noise metrics in the same regression such that we can identify any effects of different noise characteristics on housing prices. We refer to these specifications as multi-metric models, in contrast to a single metric model that solely relies on one metric, such as DNL. While the proposed metrics exhibit significant levels of correlation, Appendix Figure A2 through A4 show that the different metrics reflect distinct noise characteristics. Nevertheless, multicollinearity concerns must be taken into account in the interpretation of multi-metric models.

5 Hedonic Regression Results

5.1 Impacts of Average Noise Exposure

Table 2 summarizes the estimated elasticity of house prices to average noise exposure (coefficient β_1 in equation (3)) using a variety of econometric specifications.[20] For all airports, the first column presents estimates from a pooled OLS version of equation (3) without any controls for all the airports, which suggests that increased average noise levels lead to a decrease in house prices. Column 2 includes house characteristics, including property age, building area, house condition, etc. Column 3 adds additional neighborhood attributes (i.e., block-group level household median income, the percentage of people under 18, and the percentage of the non-white population) and distance to the nearest (dis)amenities. Column 4 also controls for seasonality by including a set of month fixed effects. Finally, column 5 adds spatial FEs. The coefficient on $\ln(DNL)$ is negative and statistically significant in all specifications.

Insert Table 2 Here

As we progressively control for house characteristics, neighborhood effects, seasonality, and other unobserved confounding factors, the elasticity of house prices to airplane noise declines in magnitude across the specifications. This suggests that failing to consider these factors might bias our estimates. Our preferred specification in column 5 implies that a 1 percent increase in DNL reduces house prices in Boston by 0.262%, 0.224% in Chicago, and 0.299% in Seattle. We test whether these estimates exhibit statistically significant differences by pooling the sample from our

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above 60 dB. See also Section 3.1.

[20] The full estimation contains a total of housing attributes in addition to the fixed effects, and commenting on each parameter estimate would take up too much space here. We suppress the reporting of the house characteristics coefficients, though they all have the expected signs and most are statistically significant; Appendix A reports the full estimation results.

three localities and testing whether the estimated coefficients by city differ. The F-test result (F = 0.16, p = 0.8492) shows that the city dummy interactions collectively do not exhibit statistically significant differences, suggesting that the average elasticity to noise exposure does not vary between markets.

To compare our results to the literature, we use the average annual noise levels in 2011 and transform the coefficient for DNL in the log-log model to the noise depreciation index (NDI), which is the percentage change in price for a one dBA change in noise levels. We find the NDI is 0.61 for the Boston sample, 0.60 for the Chicago sample, and 0.97 for the Seattle sample, which is within the range of the estimates reported by Nelson (2008); Thanos et al. (2015); Trojanek et al. (2017).

In this paper, we assume a log-log specification in equation (3). While common in the literature, it is unclear whether this specification is appropriate. We therefore test other functional forms. This is crucial since we are concentrating on the direct effects of noise exposure in urban areas and derive willingness-to-pay estimates that are particularly sensitive to the functional form. We test alternative functional forms, including semi-log functions and the Box-Cox transformation.[21] Appendix Table B1 shows the results. Columns (1) and (2) represent the semi-log and log-log model results, and columns (3)-(6) show the results from the Box-Cox transformation with different restrictions.[22] Based on the likelihood ratios, all Box-Cox results reject the linear model at the 95% confidence level (LR > 3.85). However, the ratios from the Box-Cox transformation are very similar to the log-log model. The final Box-Cox model selected in the Boston sample resulted in values of 0.205 (λ) for the dependent variable and 0.055 (θ) for the independent variables. Results from the Chicago and Seattle samples suggest similar patterns. Taken together, these results indicate that the log-log functional form reasonably represents the underlying trends.

As discussed in the above section, we assess potential conflation bias by allowing the noise coefficients to vary over our study period. We report the results using the time-invariant and time-varying models in Table 3. Comparing the estimated results between the two models for Boston, we find that the coefficients in the time-invariant model likely suffer little from conflation bias, as the

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[21] The Box-Cox transformation will be applied to the data so as to allow variation in the functional form of the dependent variable, the noise exposure, and all other control variables. The distance indices will be maintained as linear in the regression model due to the non-zero restrictions imposed by this transformation. See a more detailed discussion about functional form in hedonic studies in here.

[22] We apply various restrictions to demonstrate the performance of the Box-Cox transformation. For instance, columns (3) and (4) permit transformation only on the left-hand side and right-hand side, respectively. Columns (5) and (6) allow transformations on both sides, with column (6) permitting different parameters for each side. To test whether the Box-Cox transformation rejects the linear model, we calculate the LR statistics, which equals 2*(log likelihood of unrestricted model-log likelihood of the restricted model. The transformation rejects the linear model at a 95% confidence level if the LR statistic is larger than 3.85.

post-period interaction coefficient is similar in magnitude to the time-invariant model. Similarly, the time-invariant model in Chicago shows little evidence of downward conflation bias, and the time-invariant model in Seattle reveals little upward conflation bias. In the following robustness checks, we, therefore, use the time-invariant model as our base model to test the sensitivity of our main results.

Insert Table 3 Here

We also investigate the robustness of our estimates to alternative sets of spatial and temporal fixed effects and time trends. Appendix Table B2 reports these results. Column 1 of each table corresponds to our preferred specification in column (5) of Table 2, which uses zip-by-year fixed effects to control for spatial and temporal effects. Column 2 of Appendix Table B2 replaces zip codes with a 2-mile-by-2-mile grid. This has the advantage of using a uniform measure of spatial variation of neighborhood characteristics but may ignore historically grown neighborhood structures, which could be captured in zip code-level fixed effects. Column 3 of Appendix Table B2 uses census tracts instead of zip codes. Census tracts have the advantage of being smaller geographic areas than zip code areas; however, noise variation within census tracts is small, which makes estimating β_1 challenging. Finally, the last three columns replace the year-fixed effects with time trends. Our results point towards three insights: First, we find a negative and significant house price elasticity to noise exposure across most specifications, which demonstrates the robustness of our results to the spatial definition of fixed effects. Second, employing a finer spatial resolution for fixed effects results in limited variation in airplane noise exposure. For instance, our findings suggest that the use of census tracts as spatial units in Boston and Chicago poses challenges, as most areas exhibit minimal within-region variation of aircraft noise exposure (see Appendix Figure A6). Last, stringent time trends are likely to impose linear constraints on unobserved attributes, potentially affecting the estimation of the noise elasticity.

Appendix Table B3 shows the results for alternative housing samples. We extend our two-year sample to multiple years before 2011 and after 2016 under the assumption that there are no significant noise changes over these periods. Results suggest that the coefficients estimated are robust to such different specifications. Appendix Table B4 further shows the results for alternative sale price bounds. We restrict our sample by introducing a higher minimum price bound and a lower maximum price bound for three localities. Results show robust estimates across different specifications. Finally, we vary our choice of standard error clustering in different ways and report the results in the Appendix Table B5. Our findings remain robust across specifications.

5.2 Heterogeneity Effects of Airplane Noise Within Regions

While our results suggest that noise elasticities are similar across the three studied regions, we are interested in whether there are any heterogeneous effects of noise exposure varying across the communities that surround airports in our sample. As such, we assess whether the noise elasticity varies within each locality. We first conduct subgroup analysis by using a quantile regression approach for various housing price quantiles (q25, q50, and q75). Appendix Table B6 reports our results for each locality, indicating that the takeaways differ across localities. Home buyers in Boston exhibit a statistically significant house price elasticity to noise exposure for lower-priced homes (i.e., those in the lower quantiles) only. F-test results between groups indicate that the house price elasticity is indeed statistically different between lower-priced and middle-priced houses (F Score = 4.33, P = 0.0375) but is similar across other groups. For Chicago, we observe negative house price elasticities across various quantiles, but F-test results suggest that the reactions to noise do not statistically differ across groups. Finally, we find statistically significant house price elasticities to noise exposure for lower-priced and middle-priced houses in Seattle. Interestingly, the F-test results for Seattle only provide weak evidence for the results to differ across quantiles (F score of 3.37 and a P-value of 0.0663).

We further investigate whether these elasticities differ across various noise levels, following the approach suggested by Von Graevenitz (2018). We employ a piece-wise linear specification to allow for non-constant marginal effects across the range of airplane noise exposure levels. Such an approach could also address concerns that households may not be able to perceive aircraft noise exposure below background noise exposure levels. We segment the airplane noise variable into three intervals: $\{[\min - 40), (40 - 50], (50 - \max]\}$ dBA. Appendix Table B7 presents the results of the piece-wise linear model. We find no significant impact on housing prices for noise levels below 40 dBA for Boston and Chicago, suggesting either that such low noise exposure does not trigger any significant response or that the background noise level can mask aircraft noise at such levels. As noise levels increase, the effect on house prices becomes more pronounced. We observe a larger elasticity for noise levels above 50 dBA in Boston, though not in Chicago and Seattle, which is likely due to the limited sample size for houses at higher noise levels in the latter two cities. The explanatory power (R^2 in Appendix Table B7) of the piece-wise linear model is similar to the log-log model.

5.3 Impacts of Alternative Noise Definitions

We investigate the effects of alternative noise metrics. Appendix Table C1 shows these results for the Boston sample. Columns 1-5 report the results using different noise metrics, including average noise level (DNL), the number of noise events above 60 dBA at the peak day (MaxN60), and the percentage of days having more than 40/50/60 aircraft noise events above 60 dBA (%D(N60>40/50/60)). We find the coefficients of any noise metrics are statistically significant and negative across single-metric specifications for Boston, although they differ in magnitude given the nonlinear relationship between DNL and event-based metrics. Houses exposed to a higher frequency of overflights exceeding noise levels of 60 dBA on the peak day sell at a discount to those exposed to a lower event frequency. Houses that experienced a higher percentage of days where noise events exceeding 60 dBA more than 40/50 times a day sell at a discount to those experiencing fewer. These results are expected given the observed correlations among these noise metrics (Appendix Figure A2).

To empirically determine which noise metric best predicts residents' response to airplane noise exposure, we simultaneously include multiple noise metrics in our model. The results are reported in columns (6)-(8) of Table C1. The coefficient of DNL remains comparable in size to our baseline estimates. Conversely, the coefficients of the number of loud events on a peak day are negative but insignificant. The coefficients indicating the house price elasticity to the distribution of days with high numbers of significant aircraft noise events are mostly positive. This suggests that at the same average noise exposure level, more consistent exposure patterns (a higher share of days with a high number of high noise events) lead to lower responses in house prices. Similarly, we report the results of the Chicago and Seattle samples in Appendix Table C2 and C3. DNL continues to show a significant house price elasticity. Furthermore, the mean-preserving trends are also observed for Chicago, but not in Seattle. The latter is less surprising given Seattle's more consistent flight path patterns due to its north-south runway system. We note that these results should be interpreted with caution due to the high multicollinearity among the noise metrics.

6 Willingness to Pay for Quietness

We use the coefficients from our preferred log-log regressions to estimate the Marginal Willingness To Pay (MWTP) function for airplane noise exposure and the economic effects of the changes in airplane noise exposure over our study period. Specifically, we first estimate the MWTP and recover the individual-specific preference parameters using a second-stage specification suggested by Bajari and Benkard (2005). We then apply this second-stage specification to estimate the willingness to pay associated with reversing the changes in noise exposure over our study period in communities surrounding the three airports considered in our study.

6.1 Individual's Preference for Quietness

We estimate the MWTP using equation (3). The implicit price of a marginal 1 dBA decrease in noise exposure for each household can be calculated as:

$$MWTP_{zi} = (\frac{\partial P}{\partial DNL})_i = -\beta_1 \frac{P_i}{DNL_i}. \tag{5}$$

Figure 2 shows the distribution of MWTP for quietness[23]. For the Boston sample, the average MWTP is \$3,043.10, and the median MWTP is \$2,528.38. The positive values indicate the nature of noise exposure as a disamenity. For the Chicago sample, the average and median MWTPs are \$2,089.01 and \$1,564.67, respectively. The average and median MWTP are \$4,427.20 and \$3,235.94 in the Seattle sample. Figure 2 suggests that the distributions are skewed with a mean larger than the median (right-skewed) across the three samples. We convert the implicit prices to annual costs using the user cost of housing (5%) at the time of purchase and show the results in the upper panel of Table 4.[24] In particular, we show the deciles of the household's annualized willingness to pay for a marginal change in airplane noise. A decrease in noise level is associated with a positive willingness to pay, consistent with undesirable increases in these attributes.

Insert Figure 2 Here

When discussing these results, it is important to note that taste-based sorting behavior in the housing market often complicates welfare analysis (Mandia, 2024b,c,a). For two identical households, the household with a stronger preference for an amenity would choose different quantities than the other households in equilibrium. As a result, the estimates of the amenity could be biased. One way to address this concern is by using instruments for endogenous prices of amenities (Day et al. (2007); Zabel and Kiel (2000)).[25] Another solution is to put more structure on the model.

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[23] Our log-log functional form indicates that variations in home values and pre-period noise exposure drive heterogeneity. Interpretations of MWTP should recognize that different functional forms alter the relationship between noise exposure and property values. Therefore, tests of functional form are important—which provides the underlying reasoning for the discussions provided in the previous section.

[24] 5% is a commonly used discount in the literature. See Poterba (1984) for a discussion of converting prices to annualized user-cost measures.

[25] The most common instrumental variable strategy is based on multiple markets in time or space; however, it

Bajari and Benkard (2005) proposes to impose separability of housing attributes and the logarithmic utility structure so that there is no need to use instrumental variables. Their model does not require assumptions about the distribution of unobservable idiosyncratic preference parameters or impose restrictions on household sorting. The utility function for household i is assumed to be:

$$U_i(h(x_i, z_i), c_i) = \sum_k \beta_{ki} log(x_{ki}) + \beta_z log(N - z_i) + c_i, \tag{6}$$

where $h(x, z)$ is the housing good, c is a numeraire good, z is noise exposure, and x is a vector of house and neighborhood characteristics. We choose N to be one dBA larger than the maximum noise observed to ensure quiet gives a positive utility to households. Applying the first-order condition of utility maximization and considering equation 5, an individual's preferences for quietness are:[26]

$$\beta_{zi} = -\frac{\partial P_i}{\partial Noise_i}(N - z_i) = -MWTP_i(N - z_i). \tag{7}$$

Table 4 also reports the annual noise preference parameters, which are calculated using the yearly implicit price and the observed amount of the amenity consumed. We find substantial variation both within and across localities in preference parameters. The average preference parameter for the Boston sample is 4441.89, and the median is 3626.46. The average and median for the Chicago sample are 2439.87 and 1654.82, respectively. The average and median for the Seattle sample are 6940.03 and 4369.85, respectively. Similarly to MWTP, the distribution of preference on noise is highly skewed, with a mean much larger than the median.

Insert Table 4 Here

Based on these preference parameters, we analyze how preferences for quietness are correlated with demographics. For this purpose, we regress the log of the parameter on social demographics such as income and race. Linking the house transaction records with household demographics has been carried out in recent papers. However, most studies matched less than 50% of the sample to demographic data (Bishop and Timmins, 2018). Thus, rather than combining the individual preference parameters with property-level demographics, we consolidate our transaction data at the census block group level. We then pair it with median household incomes and the percentage of the

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requires the absence of taste-based sorting across markets to be valid and, simultaneously, enough variation in the marginal price function across markets for the instruments to be strong.

[26] Note that here and in the following, we define preference for quietness as the preference for avoiding aviation noise exposure.

non-white population at the same census block group level. This leads to the following equation:

$$log(\beta_c) = \alpha_0 + \alpha_1 Inc_c + \alpha_2 NW_c + \epsilon_c \tag{8}$$

where β_c is the average annual preference in census block group c; Inc_c is the median household income for census block group c; NW_c is the percentage of non-white population for census block group c. If α_1 or α_2 were positive, households living in higher-income or larger-nonwhite-population census block groups are associated with a stronger taste for quietness.

Insert Table 5 Here

We report our results in Table 5. Across all three localities, household income is associated with a stronger taste for quietness. Specifically, a one-thousand dollar increase in median household income is associated with a 0.8%-1.6% increase in preference parameter. The taste for quietness also decreases with the percentage of the non-white population in the census block group. These findings are consistent with Depro et al. (2015). In total, the selected observable characteristics of the household explain around 29-35 percent of the variation in taste for quietness across localities.

6.2 Economic Effects of Airplane Noise

We use the demand function for airplane noise and estimate the economic effects of airplane noise for communities surrounding the three airports considered in our study. For each household in the study sample, we calculate the willingness to pay for a non-marginal change in noise exposure from z^1 to z^0 by comparing the change in the Hicksian composite good required to equate utility levels before and after changes in noise exposure. In particular, we here compute the capitalized WTP associated with the observed noise exposure changes over the study period:

$$WTP_i = \beta_{zi}(log(N - z_i^1) - log(N - z_i^0)) \tag{9}$$

Figure 3 reports our estimates for the willingness to pay associated with reverting to year-2011 exposure, which is heterogeneous both within and across the three localities. A positive WTP indicates that a household is willing to pay to revert to 2011 noise exposure, whereas a negative value indicates that the household would require compensation to return to 2011 exposure.

Figure 3b shows the distribution of the WTP in Boston. Around 84% of the households in the sample show a positive WTP due to an increase in the disamenity over the study period. The distribution of WTP can be traced back to changes in flight paths and to the differences in preference parameter (see equation 5). We find a larger WTP for reverting to the 2011 baseline along flight paths with increased noise exposure, especially to the Northwest and West of the airport. Comparing Figure 3a to Figure 1a shows that the preference parameter has a substantial impact on the WTP estimates. Following our discussion in the previous section, it is not surprising to find attenuated WTP estimates in the more affluent Boston Metrowest neighborhoods.

In Chicago, communities in the south, northwest, and northeast of the airport benefit from the reduced noise exposure, whereas the communities west and east of the runway observe higher noise exposure (see Figure 1b). The WTP estimates indicate pronounced noise reduction benefits in the high-income coastal areas north of the city (see Figure 3c). Overall, our results suggest that Chicago households would require a compensation of \$122.2 for a reversal to exposure paths in 2011, with 68 percent of households exhibiting such a compensation requirement (see Figure 3d).

The WTP to revert to 2011 noise exposure levels for households in Seattle is less heterogeneous. 95% of households would show a relatively small capitalized WTP, while a small region in the northern areas benefits from the changes. The average household in the Seattle sample would have a WTP of \$168.37 (see Figures 3e and 3f).

Insert Figure 3 Here

7 Conclusion

In this paper, we develop a framework for estimating the contemporaneous effect of airplane noise exposure on housing prices using quasi-random variations in local airplane noise exposure driven by adopting new air navigation technology and changes in runway configuration. We focus on three urban areas—Boston, Massachusetts; Chicago, Illinois; and Seattle, Washington—and employ a hedonic difference-in-difference approach to estimate the welfare implications of airplane noise. Our results show that an additional decibel increase in annual average DNL is associated with a decrease in the sales prices of residential homes in three localities of roughly 0.6-1.0 percent. We conclude that preferences for airplane noise are consistent across geographic regions. Decomposing the noise exposure into different metrics, we find that DNL captures the house price impacts well. We interpret these findings as evidence that the returns from regulating average noise levels exceed those from regulating the frequency of loud events and variation of daily noise event frequency, at least for the population that comprises our sample.

Our findings indicate significant variation within and across the three regions in the annual implicit prices recovered from the first stage of the hedonic model. The average annualized MWTP for one dBA reduction in noise exposure in Boston is \$152.15, while the median is \$126.42. There is considerable heterogeneity, as evidenced by the interquartile range of \$96.5. The means in Chicago and Seattle are \$104.45 and \$221.36, respectively, with an interquartile range of \$71.75 and \$167.66. We find the underlying preferences for avoiding aircraft noise exposure to be heterogeneous and to be correlated with sociodemographic characteristics. Most importantly, a higher preference for quietness is correlated with higher income levels. As a result, we find the WTP associated with reverting to year-2011 noise exposure levels to vary across households, with the highest WTP observed in neighborhoods with high noise exposure change and higher income levels. In addition, we note that both Seattle and Boston are faced with most households having a WTP to pay to return to 2011 exposure (given increased noise exposure), whereas the average Chicago household would need to be compensated to return to 2011 exposure.

Since the FAA introduced its PBN strategy in the "Roadmap for Performance-Based Navigation" in 2003, PBN procedures have been studied and implemented across the United States. These procedures offer numerous benefits, including more direct flight paths, reduced fuel consumption, and lower emissions. In a cost-benefit analysis, such benefits must be weighed against potential costs, which would include any increases in noise exposure for residents of communities surrounding airports. Such noise concerns have been brought forward in the public debate. Our results reveal the prevalence of such impacts using the housing price metric, showing complex patterns. Enhancing comprehension of airplane noise shifts in sensitive neighborhoods could aid policymakers in better conducting such cost-benefit analyses going forward.

We note several open questions that merit additional study. By now, roughly 3,165 airports in the FAA's National Plan of Integrated Airport Systems (NPIAS) in the NAS have at least one published PBN Procedure. The determinants of such procedures, including exogeneity of procedure design, is assumed in this study, but might warrant future analysis. Second, the current study did not account for the impact of weather on residents' airplane noise exposure; utilizing more advanced modeling techniques could be beneficial in investigating this aspect. Third, research to better understand the distributional effects of airplane noise could help policymakers serve particularly sensitive households. Finally, research could explore how the PBN procedures affect local air pollution and health outcomes for residents under the new flight path. Future work could pair the changes in regional air pollution with health outcomes to enhance the understanding of the social costs of airplane externalities.

References

Allroggen, F. and R. Malina (2014). Do the regional growth effects of air transport differ among airports? *Journal of Air Transport Management 37*, 1–4.

Bajari, P. and C. L. Benkard (2005). Demand estimation with heterogeneous consumers and unobserved product characteristics: A hedonic approach. *Journal of Political Economy 113*(6), 1239–1276.

Banzhaf, H. S. (2021). Difference-in-differences hedonics. *Journal of Political Economy 129*(8), 2385–2414.

Bayer, P., N. Keohane, and C. Timmins (2009). Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management 58*(1), 1–14.

Bishop, K. C. and C. Timmins (2018). Using panel data to easily estimate hedonic demand functions. *Journal of the Association of Environmental and Resource Economists 5*(3), 517–543.

Black, D. A., J. A. Black, T. Issarayangyun, and S. E. Samuels (2007). Aircraft noise exposure and resident's stress and hypertension: A public health perspective for airport environmental management. *Journal of Air Transport Management 13*(5), 264–276.

Black, S. E. (1999). Do better schools matter? parental valuation of elementary education. *The Quarterly Journal of Economics 114*(2), 577–599.

Boes, S. and S. Nüesch (2011a). Quasi-experimental evidence on the effect of aircraft noise on apartment rents. *Journal of Urban Economics 69*(2), 196–204.

Boes, S. and S. Nüesch (2011b). Quasi-experimental evidence on the effect of aircraft noise on apartment rents. *Journal of Urban Economics 69*(2), 196–204.

Boes, S., S. Nüesch, and S. Stillman (2013). Aircraft noise, health, and residential sorting: Evidence from two quasi-experiments. *Health Economics 22*(9), 1037–1051.

Button, K. and J. Yuan (2013). Airfreight transport and economic development: An examination of causality. *Urban Studies 50*(2), 329–340.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? evidence from the housing market. *Journal of Political Economy 113*(2), 376–424.

Cohen, J. P. and C. C. Coughlin (2009). Changing noise levels and housing prices near the atlanta airport. *Growth and Change 40*(2), 287–313.

Currie, J., L. Davis, M. Greenstone, and R. Walker (2015). Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings. *American Economic Review 105*(2), 678–709.

Davis, L. W. (2011). The effect of power plants on local housing values and rents. *Review of Economics and Statistics 93*(4), 1391–1402.

Day, B., I. Bateman, and I. Lake (2007). Beyond implicit prices: recovering theoretically consistent and transferable values for noise avoidance from a hedonic property price model. *Environmental and Resource Economics 37*, 211–232.

Dean, J. T. (2024). Noise, cognitive function, and worker productivity. *American Economic Journal: Applied Economics 16*(4), 332–60.

Depro, B., C. Timmins, and M. O'Neil (2015). White flight and coming to the nuisance: can residential mobility explain environmental injustice? *Journal of the Association of Environmental and resource Economists 2*(3), 439–468.

Eagan, M. E., R. Hanrahan, and R. Miller (2013). Implementing performance-based navigation procedures at us airport: improving community noise exposure. In *INTER-NOISE and NOISE-CON Congress and Conference Proceedings*, Volume 247, pp. 1577–1586. Institute of Noise Control Engineering.

El-Fadel, M., M. Chahine, H. Baaj, and T. Mezher (2002). Assessment of noise impacts at airports. *International journal of environmental studies 59*(4), 447–467.

Friedt, F. L. and J. P. Cohen (2021). Valuation of noise pollution and abatement policy: Evidence from the minneapolis-st. paul international airport. *Land Economics 97*(1), 107–136.

Gayer, T., J. T. Hamilton, and W. K. Viscusi (2000). Private values of risk tradeoffs at superfund sites: housing market evidence on learning about risk. *Review of Economics and Statistics 82*(3), 439–451.

Grampella, M., G. Martini, D. Scotti, F. Tassan, and G. Zambon (2017). Determinants of airports' environmental effects. *Transportation Research Part D: Transport and Environment 50*, 327–344.

Greenstone, M. and J. Gallagher (2008). Does hazardous waste matter? evidence from the housing market and the superfund program. *The Quarterly Journal of Economics 123*(3), 951–1003.

Grineski, S., B. Bolin, and C. Boone (2007). Criteria air pollution and marginalized populations: environmental inequity in metropolitan phoenix, arizona. *Social Science Quarterly 88*(2), 535–554.

Grobler, C., P. J. Wolfe, K. Dasadhikari, I. C. Dedoussi, F. Allroggen, R. L. Speth, S. D. Eastham, A. Agarwal, M. D. Staples, J. Sabnis, et al. (2019). Marginal climate and air quality costs of aviation emissions. *Environmental Research Letters 14*(11), 114031.

He, Q., C. Wollersheim, M. Locke, and I. Waitz (2014). Estimation of the global impacts of aviation-related noise using an income-based approach. *Transport Policy 34*, 85–101.

Hegewald, J., M. Schubert, A. Freiberg, K. Romero Starke, F. Augustin, S. G. Riedel-Heller, H. Zeeb, and A. Seidler (2020). Traffic noise and mental health: a systematic review and meta-analysis. *International Journal of Environmental Research and Public Health 17*(17), 6175.

Hume, K. I., M. Brink, and M. Basner (2012). Effects of environmental noise on sleep. *Noise and health 14*(61), 297–302.

Jensen, L., J. Thomas, C. Brooks, M. Brenner, and R. J. Hansman (2017). Analytical approach for quantifying noise from advanced operational procedures. In *USA/Europe Air Traffic Management Research and Development Seminar.*

Kopsch, F. (2016). The cost of aircraft noise–does it differ from road noise? a meta-analysis. *Journal of Air Transport Management 57*, 138–142.

Kuminoff, N. V., C. F. Parmeter, and J. C. Pope (2010). Which hedonic models can we trust to recover the marginal willingness to pay for environmental amenities? *Journal of Environmental Economics and Management 60*(3), 145–160.

Kwak, K. M., Y.-S. Ju, Y.-J. Kwon, Y. K. Chung, B. K. Kim, H. Kim, and K. Youn (2016). The effect of aircraft noise on sleep disturbance among the residents near a civilian airport: a cross-sectional study. *Annals of Occupational and Environmental Medicine 28*(1), 1–10.

Levesque, T. J. (1994). Modelling the effects of airport noise on residential housing markets: a case study of winnipeg international airport. *Journal of Transport Economics and Policy*, 199–210.

Mandia, J. (2024a). Capitalization of noise pollution and environmental justice: Evidence from changes to flight paths. Working paper.

Mandia, J. (2024b). Disentangling information frictions and endogenous amenities in residential sorting models: Evidence from changes in noise pollution exposure. Working paper.

Mandia, J. (2024c). Valuing noise pollution in a residential sorting model: Evidence from changes to flight paths. Working paper.

McMillen, D. P. (2004). Airport expansions and property values: the case of chicago o'hare. *Journal of Urban Economics 55*(3), 627–640.

McMillen, D. P. and J. McDonald (2004). Reaction of house prices to a new rapid transit line: Chicago's midway line, 1983–1999. *Real Estate Economics 32*(3), 463–486.

Nakamura, D. and W. Royce (2008). Operational benefits of performance-based navigation. *Boeing Aero Quarterly, Quarter 2*, p13–21.

Nelson, J. P. (2004). Meta-analysis of airport noise and hedonic property values. *Journal of Transport Economics and Policy (JTEP) 38*(1), 1–27.

Nelson, J. P. (2008). Hedonic property value studies of transportation noise: aircraft and road traffic. In *Hedonic Methods in Housing Markets*, pp. 57–82. Springer.

Nguy, A., C. Sun, and S. Zheng (2014). Airport noise and residential property values: Evidence from beijing. In *Proceedings of the 17th International Symposium on Advancement of Construction Management and Real Estate*, pp. 473–481. Springer.

Nolte, C., K. J. Boyle, A. M. Chaudhry, C. M. Clapp, D. Guignet, H. Hennighausen, I. Kushner, Y. Liao, S. Mamun, A. Pollack, et al. (2021). Studying the impacts of environmental amenities and hazards with nationwide property data: best data practices for interpretable and reproducible analyses. *WVU College of Law Research Paper* (2021-013).

Nourse, H. O. (1967). The effect of air pollution on house values. *Land Economics 43*(2), 181–189.

O'Hare Noise Compatibility Commission (2025). O'hare modernization program – runway changes: 10c/28c, 10r/28l, 14l/32r. Technical report, O'Hare Noise Compatibility Commission. Runway 10C/28C commissioned October 17, 2013; Runway 14L/32R closed in 2015; Runway 10R/28L opened October 15, 2015.

Ossokina, I. V. and G. Verweij (2015). Urban traffic externalities: Quasi-experimental evidence from housing prices. *Regional Science and Urban Economics 55*, 1–13.

Parmeter, C. F., D. J. Henderson, and S. C. Kumbhakar (2007). Nonparametric estimation of a hedonic price function. *Journal of Applied Econometrics 22*(3), 695–699.

Parmeter, C. F. and J. C. Pope (2013). Quasi-experiments and hedonic property value methods. In *Handbook on Experimental Economics and the Environment*. Edward Elgar Publishing.

Percoco, M. (2010). Airport activity and local development: Evidence from italy. *Urban Studies 47*(11), 2427–2443.

Peters, J. L., C. D. Zevitas, S. Redline, A. Hastings, N. Sizov, J. E. Hart, J. I. Levy, C. J. Roof, and G. A. Wellenius (2018). Aviation noise and cardiovascular health in the united states: A review of the evidence and recommendations for research direction. *Current Epidemiology Reports 5*, 140–152.

Phaneuf, D. J., V. K. Smith, R. B. Palmquist, and J. C. Pope (2008). Integrating property value and local recreation models to value ecosystem services in urban watersheds. *Land Economics 84*(3), 361–381.

Pope, J. C. (2008). Buyer information and the hedonic: the impact of a seller disclosure on the implicit price for airport noise. *Journal of Urban Economics 63*(2), 498–516.

Poterba, J. M. (1984). Tax subsidies to owner-occupied housing: an asset-market approach. *The Quarterly Journal of Economics 99*(4), 729–752.

Pratt, G. C., M. L. Vadali, D. L. Kvale, and K. M. Ellickson (2015). Traffic, air pollution, minority and socio-economic status: addressing inequities in exposure and risk. *International Journal of Environmental Research and Public Health 12*(5), 5355–5372.

Ragettli, M. S., S. Goudreau, C. Plante, S. Perron, M. Fournier, and A. Smargiassi (2016). Annoyance from road traffic, trains, airplanes and from total environmental noise levels. *International journal of environmental research and public health 13*(1), 90.

Roof, C., A. Hansen, G. Fleming, T. Thrasher, A. Nguyen, C. Hall, E. Dinges, F. Grandi, B. Kim, S. Usdrowski, et al. (2007). Aviation environmental design tool (aedt) system architecture. Technical report, United States. Federal Aviation Administration. Office of Environment and Energy.

Rosen, S. (1974). Hedonic prices and implicit markets: product differentiation in pure competition. *Journal of Political Economy 82*(1), 34–55.

Schlenker, W. and W. R. Walker (2016). Airports, air pollution, and contemporaneous health. *The Review of Economic Studies 83*(2), 768–809.

Stansfeld, S., S. Hygge, C. Clark, T. Alfred, et al. (2010). Night time aircraft noise exposure and children's cognitive performance. *Noise and Health 12*(49), 255.

Thanos, S., A. L. Bristow, and M. R. Wardman (2015). Residential sorting and environmental externalities: the case of nonlinearities and stigma in aviation noise values. *Journal of regional science 55*(3), 468–490.

Theebe, M. A. (2004). Planes, trains, and automobiles: the impact of traffic noise on house prices. *The Journal of Real Estate Finance and Economics 28*, 209–234.

Timar, S., R. Varani, B. Townsend, and W. MacKenzie (2017). Procedure design and execution of pbn instrument flight procedures. Technical report, Airport Cooperative Research Program, Transportation Research Board. PBN trajectories must balance safety, capacity, efficiency, fuel burn, noise, and emissions.

Trojanek, R., J. Tanas, S. Raslanas, and A. Banaitis (2017). The impact of aircraft noise on housing prices in poznan. *Sustainability 9*(11), 2088.

Tsui, W. H. K., D. T. W. Tan, and S. Shi (2017). Impacts of airport traffic volumes on house prices of new zealand's major regions: A panel data approach. *Urban Studies 54*(12), 2800–2817.

U.S. Government Accountability Office (2021). Faa implementation of performance-based navigation (pbn). *GAO Report*. FAA began PBN implementation in major metropolitan areas starting in 2013.

Von Graevenitz, K. (2018). The amenity cost of road noise. *Journal of Environmental Economics and Management 90*, 1–22.

WSP (2025). O'hare international airport modernization program (omp). Website. Accessed: 2025-10-15.

Zabel, J. E. and K. A. Kiel (2000). Estimating the demand for air quality in four us cities. *Land Economics*, 174–194.

Table 1: Summary Statistics for Housing, Noise, Neighborhoods

	Boston Logan (N=21,989)		Chicago O'Hare (N=33,913)		Seattle Tacoma (N=30,136)	
	Mean	SD	Mean	SD	Mean	SD
Sale Price ($2011)						
2011 Price ($K)	447.40	301.99	302.05	247.86	346.22	276.44
2016 Price ($K)	553.01	305.11	340.24	232.51	441.59	278.04
DNL (dB)						
2011 DNL	42.96	5.89	37.32	5.02	30.91	9.45
2016 DNL	46.33	5.90	36.24	5.59	32.11	9.51
Housing Characteristics						
Age	78.94	37.30	57.19	28.10	34.55	27.90
No Of Stories	2.06	0.58	1.50	0.43	1.55	0.53
Total Bath	2.37	1.04	1.83	1.01	2.01	0.80
Total Bedrooms	3.87	1.56	3.28	0.80	3.14	1.03
Lot Size (ft^2)	9303.14	12480.71	7843.84	4720.33	11961.91	13537.43
Basement Dummy	0.46	0.50	0.03	0.17	0.32	0.46
Fireplace Dummy	.	.	.	.	0.42	0.49
Average Condition Dummy	0.62	0.49	.	.	0.37	0.48
Excellent Condition Dummy	0.03	0.18	.	.	0.02	0.12
Fair Condition Dummy	0.02	0.15	.	.	0.10	0.30
Pool Dummy	0.03	0.16	.	.	.	.
Neighborhood Char. (2011)						
Block group median income ($K)	85.65	38.75	82.69	39.77	76.24	32.95
Block group under 18 (%)	19.55	7.80	22.29	7.41	19.71	8.06
Block group non-white (%)	21.59	22.49	24.08	21.72	34.44	19.49
Distance Index to Local Amenities						
City Hall	0.86	0.09	0.03	0.13	0.01	0.09
Road	0.31	0.39	0.21	0.34	0.16	0.31
Rail	0.17	0.32	0.15	0.30	0.03	0.14
Shopping Mall	0.01	0.07	0.01	0.06	0.02	0.12
Open Space	0.10	0.27	0.03	0.14	0.08	0.23
Coastal Line	0.02	0.12	0.00	0.03	0.03	0.15

Notes: This table reports summary statistics for the key variables included in the analysis for Boston Logan, Chicago O'Hare, and Seattle Tacoma Airports. Columns 1-2, 3-4, and 5-6 report means and standard deviations for every variable in the Boston, Chicago, and Seattle datasets, respectively. Odd and even columns are the means and standard deviations for these three data samples, respectively. House transaction prices and characteristics in three urban areas are obtained from the ZTRAX database. Distance indices are calculated based on the linear distance from each house to the nearest amenity location and a spatial decay function in equation (2).

Table 2: Hedonic Regression Results: DNL Impacts

	(1)	(2)	(3)	(4)	(5)
Boston Logan Airport					
ln(DNL)	-0.968***	-0.822***	-0.453***	-0.446***	-0.262***
	(0.028)	(0.028)	(0.027)	(0.027)	(0.048)
Observations	21989	21133	20838	20838	20835
Chicago O'Hare Airport					
ln(DNL)	-0.748***	-0.193***	-0.104***	-0.098***	-0.224***
	(0.023)	(0.019)	(0.017)	(0.017)	(0.044)
Observations	33913	33636	33340	33340	33326
Seattle Tacoma Airport					
ln(DNL)	-0.432***	-0.313***	-0.155***	-0.154***	-0.299***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.062)
Observations	30136	30136	29886	29886	29882
House Characteristics		Yes	Yes	Yes	Yes
Neighborhood			Yes	Yes	Yes
Month FEs				Yes	Yes
Spatial FEs					Yes

Notes: Each column represents a separate regression. Column 1 includes no controls. Column 2 includes additional house characteristics. Column 3 adds additional neighborhood attributes and distance to the nearest city hall, highway, railroad, coastal line, shopping mall, and open space. Column 4 controls for seasonality. Column 5 adds additional spatial FEs. For the Boston and Chicago areas, we use zip-code-by-year FEs. For the Seattle area, we use census-tract-by-year FEs. The dependent variable is the log of property transaction prices in 2011 and 2016. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 3: Hedonic Regression Results: Time-invariant and Time-varying Model Comparison

	Boston Logan Airport		Chicago O'hare Airport		Seattle Tacoma Airport	
	(1A)	(1B)	(2A)	(2B)	(3A)	(3B)
Time Invariant Gradient						
ln(DNL)	-0.262*** (0.048)		-0.224*** (0.044)		-0.299*** (0.062)	
Time Variant Gradient						
ln(DNL) X PRE		-0.374*** (0.079)		-0.244*** (0.077)		-0.238** (0.100)
ln(DNL) X POST		-0.235*** (0.059)		-0.213*** (0.054)		-0.322*** (0.078)
Observations	20835	20835	33326	33326	29882	29882

Notes: Each column represents a separate regression. Model A uses a time-invariant hedonic price function, while model B allows all coefficients to vary over time. The dependent variable is the log of property transaction prices in 2011 and 2016. All specifications include spatial and monthly fixed effects, house and neighborhood characteristics controls, and distance to the nearest city hall, highway, railroad, shopping mall, coastal line, and open space. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Annualized MWTP Price and Preference Parameters in three localities

Annualized MWTP	10th P	25th P	Median	75th P	90th P	Mean
Boston Logan Airport	58.53	83.90	119.63	175.03	262.50	143.85
Chicago O'Hare Airport	35.20	51.89	77.09	122.57	199.08	102.87
Seattle Tacoma Airport	63.85	99.69	160.72	264.23	443.65	218.27
Preference parameter β_i	10th P	25th P	Median	75th P	90th P	Mean
Boston Logan Airport	1387.80	2267.17	3626.46	5586.96	8466.16	4441.89
Chicago O'hare Airport	617.70	988.04	1654.82	2887.18	5093.49	2439.87
Seattle Tacoma Airport	1093.89	2159.47	4369.85	8497.75	15710.52	6940.03

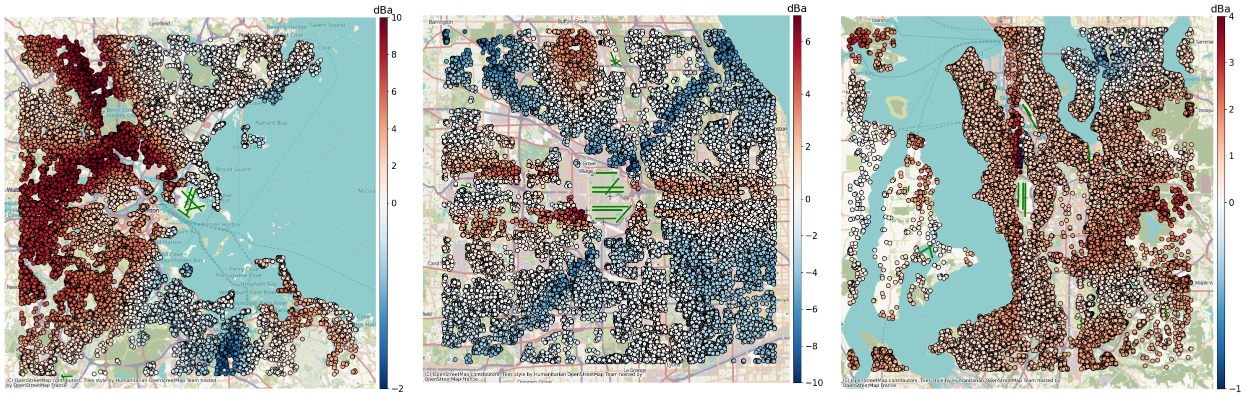
Notes: The table displays annual implicit prices and preference parameters by airports. Annual implicit prices are calculated based on the user cost of housing (5% of housing prices) for those homes in the 20x20 nautical mile geospace in three localities. These estimates reveal the 10%-90% of the household's willingness to pay for a marginal change in the airplane noise. A decrease in noise levels is associated with a positive willingness to pay, consistent with increases in these attributes being undesirable. All prices are at 2011 levels. The household's preference parameter, β_i is calculated using the annual implicit price and the observed amount of the amenity consumed (see Equation (7)). The 10%-90% of the recovered preference parameter for quietness is shown in the bottom panel of the table for each locality.

Table 5: Preference Parameter and Demographics

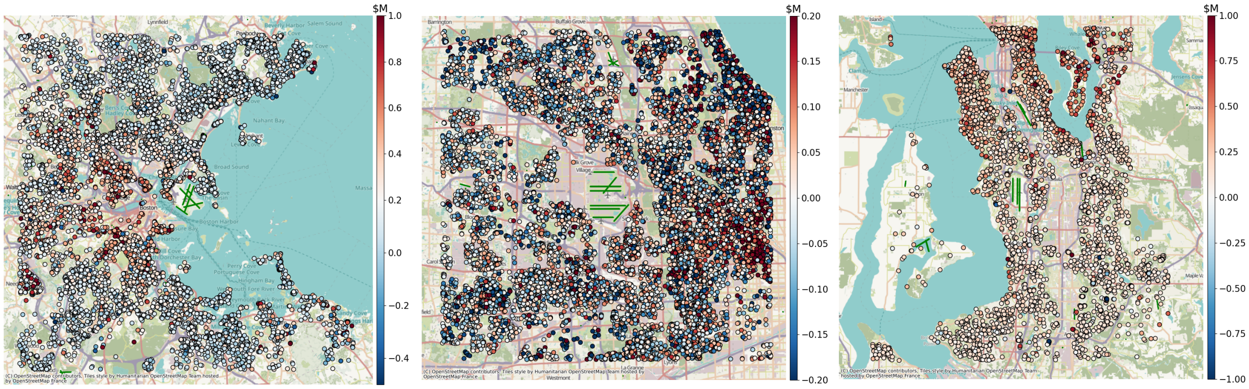
	BOS	ORD	SEA
Median HH. Income ($K)	0.008***	0.009***	0.016***
	(0.000)	(0.000)	(0.001)
Non-white Population (%)	-0.004***	-0.003***	-0.005***
	(0.000)	(0.000)	(0.001)
Observations	2955	3765	1537
Adjusted R2	0.311	0.296	0.347

Notes: This table reports the results of the preference decomposition relating the preference parameter for quiet to household observable characteristics using equation (8). The dependent variable is the log of the preference parameter in columns (1)-(3). * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

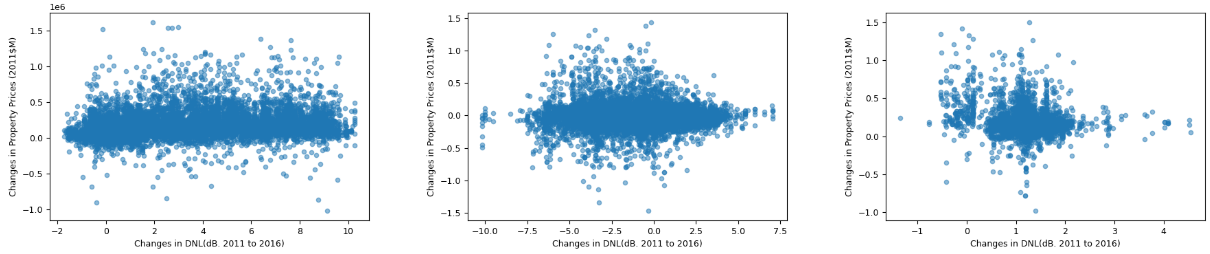
Figure 1: DNL Changes, House Price Changes, Correlation in Three Regions



(a) Δ DNL in BOS (b) Δ DNL in ORD (c) Δ DNL in SEA



(d) Δ Housing Price in BOS (e) Δ Housing Price in ORD (f) Δ Housing Price in SEA

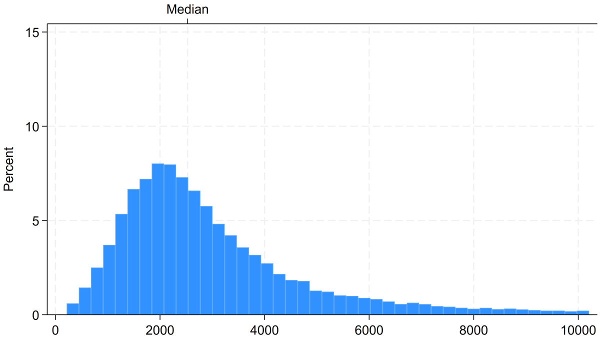


(g) Correlation in BOS (h) Correlation in ORD (i) Correlation in SEA

Notes: Changes are shown by property in the sample (dots). There are too few repeat sales to support the noise and housing price comparison between 2011 and 2016. Here, we compare the average housing prices sold three years before 2011 and after 2016. For DNL, we compare its changes for houses sold at least once. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index.

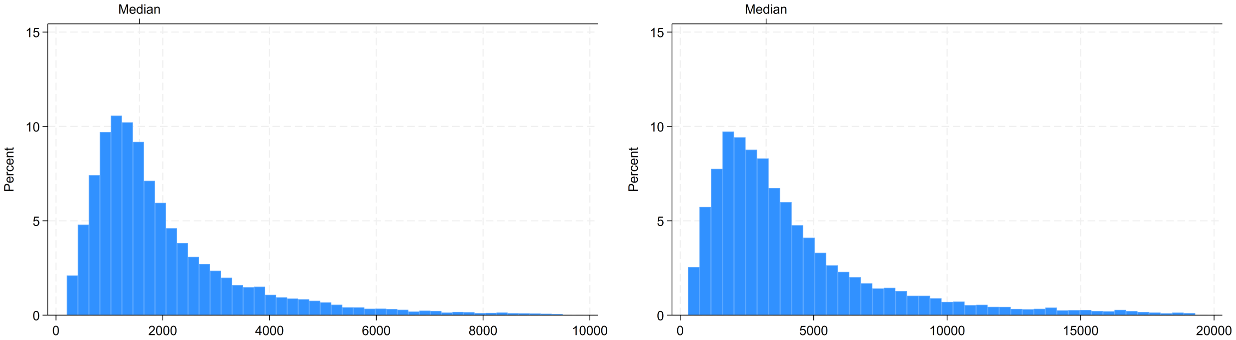
Figure 2: Distribution of MWTP Estimates of Quietness

(a) Boston Logan Airport



(b) Chicago O'Hare Airport

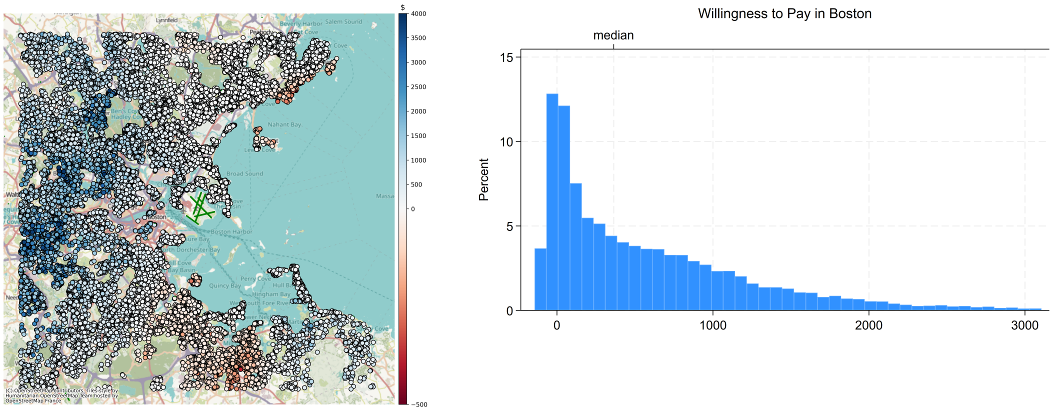
(c) Seattle Tacoma Airport



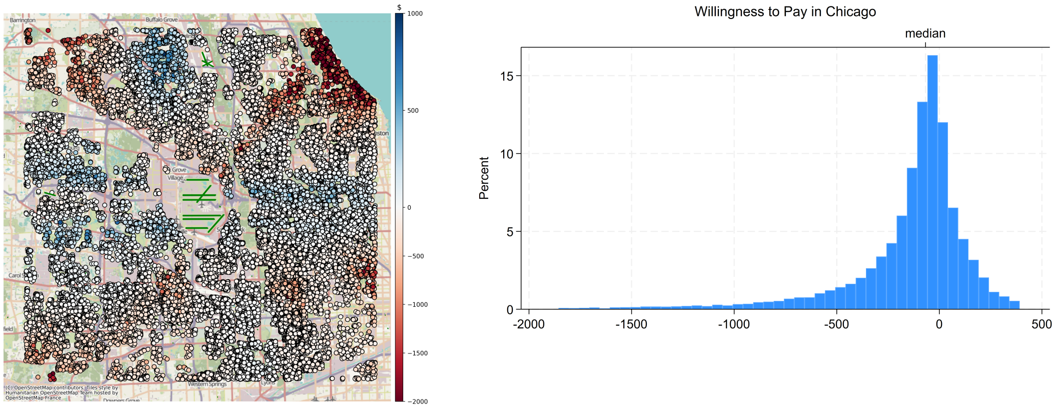
Notes: This figure shows the distribution of marginal willingness-to-pay (MWTP) estimates for reductions in aircraft noise (quietness) using equation (6) around three major airports: Boston Logan, Chicago O'Hare, and Seattle Tacoma. The horizontal axis reports MWTP in 2011 US dollars, and the vertical axis reports the percentage of the empirical distribution.

Figure 3: WTP to revert from 2016 to 2011 noise exposure

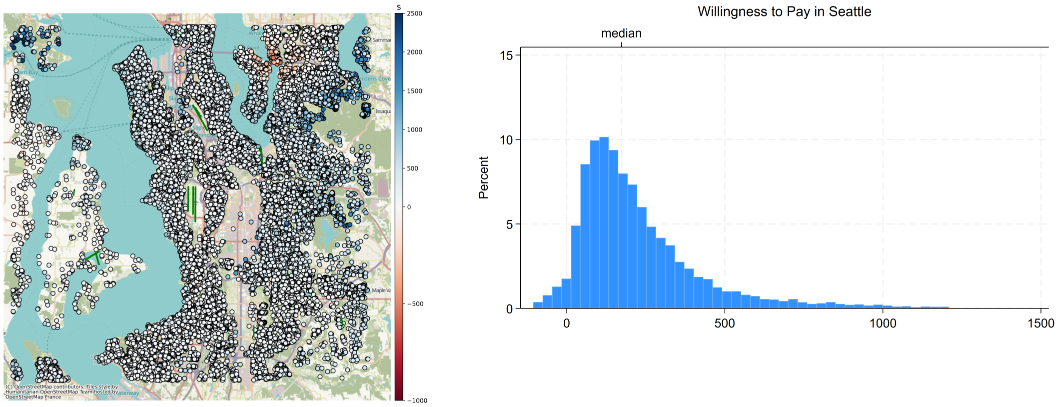
(a) Boston Logan Airport (b) Boston Logan Airport



(c) Chicago O'Hare Airport (d) Chicago O'Hare Airport



(e) Seattle Tacoma Airport (f) Seattle Tacoma Airport



Notes: This figure presents the estimated willingness to pay (WTP) for reverting from 2016 to 2011 aircraft noise exposure levels around Boston Logan, Chicago O'Hare, and Seattle Tacoma airports. Panels (a), (c), and (e) map the spatial distribution of household-level WTP, while panels (b), (d), and (f) report the corresponding histograms of WTP distributions. Positive values indicate households' willingness to pay to avoid increased noise disamenities over the study period, whereas negative values reflect compensation requirements for reverting to the 2011 baseline when noise exposure declined.

Planes Overhead: How Airplane Noise Impacts Home Values

Florian Allroggen, R. John Hansman, Christopher R. Knittel, Jing Li, Xibo Wan, and Juju Wang

Supplemental Appendices

These appendices supplement our article “Planes Overhead: How Airplane Noise Impacts Home Values” with the following material:

- Supplemental Appendix A includes data details on noise exposures, the correlation between alternative noise metrics, data details on house transactions and assessment data, the matching process between house addresses and noise grids, and spatial resolution discussion.

- Supplemental Appendix B contains robustness checks on results from our preferred model.

  Appendix C provides additional findings on the effects of alternative noise metrics.

Appendix

Supplemental Appendix A Data Details and Additional Evidence

Supplemental Appendix A.1 Data Details: Noise Metrics

The process of generating noise output at the grid level around airports using the AEDT (Aviation Environmental Design Tool) model involves several steps(Roof et al., 2007). First, we define the study area, specifying the geographic region of interest. Next, airport and flight data are input into the model, including information such as runway configurations, aircraft types, flight schedules, and air traffic data. Grid settings are then configured, determining the size and resolution of the grid used for analysis. With all the necessary inputs in place, the noise simulation is initiated within the AEDT model, incorporating the flight data, airport characteristics, and atmospheric conditions to calculate noise levels generated by aircraft operations. The output obtained from the simulation provides detailed noise information at the grid level, including noise contours and specific noise levels within each grid cell. These data can be further analyzed to assess noise exposure and evaluate the impact of aircraft activities on the surrounding environment[27].

To construct our measure of noise exposure, we consider not only the cumulative noise measures, such as day-night average sound level, but also the intensity of extremely loud events and the duration of these loud events as factors influencing residential property prices. We annualized the daily day-night average sound level by calculating the cumulative noise exposures over a year, penalizing each nighttime operation as we did in the daily DNL calculation. Since we do not have a full-year coverage of observations on daily DNL, we utilize as many daily DNLs as possible each year and generate annual DNL measures. We use the number of events that exceed a certain noise level on the peak day over a year at a location to represent the intensity of extremely loud events. We consider the number of days over a year with noise events exceeding a certain noise level multiple times at a location to represent the duration of these loud events.

To determine the noise threshold that best reflects households' response to airplane noise exposure, we closely follow the findings by Jensen et al. (2017) and consider 60 dBA a good indicator of annoyance towards airplane noise. We use 60 dBA as the noise threshold to construct five unique noise metrics and explore their impacts on housing prices in three localities. Figures A2-A4 show the correlation of noise metrics in three localities.

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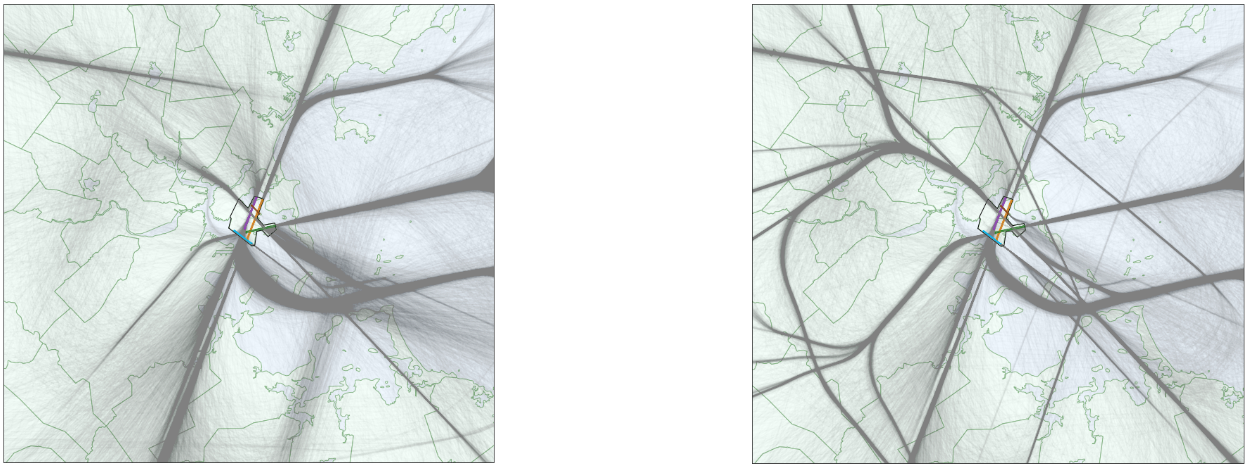
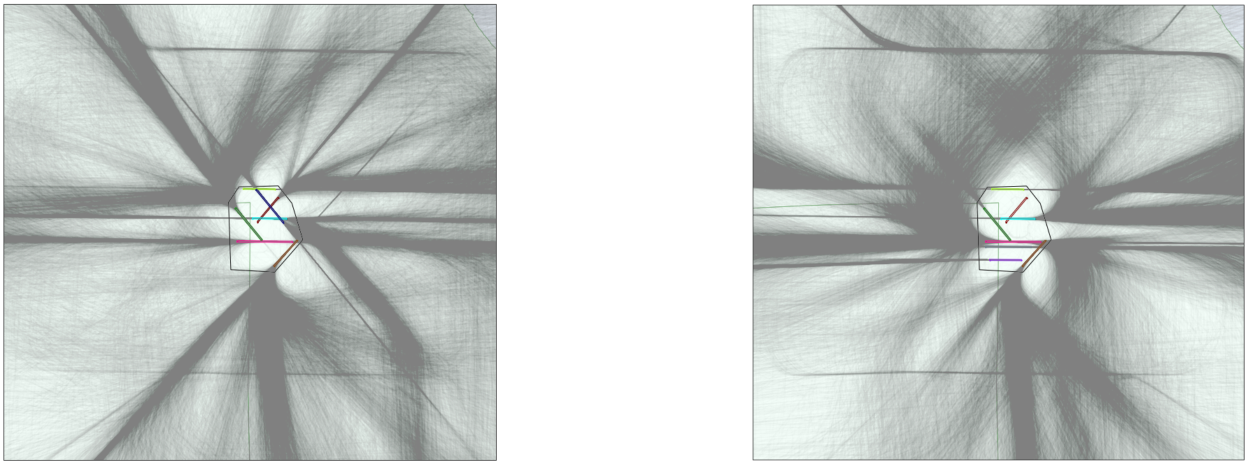
[27] For specific guidance on using the AEDT model effectively, please refer to the AEDT user manual or relevant documentation is recommended.

Figure A1: Flight Track Changes from 2011 to 2016 in three localities

(a) Boston (2011) (b) Boston (2016)



(c) Chicago (2011) (d) Chicago (2016)



(e) Seattle (2011) (f) Seattle (2016)

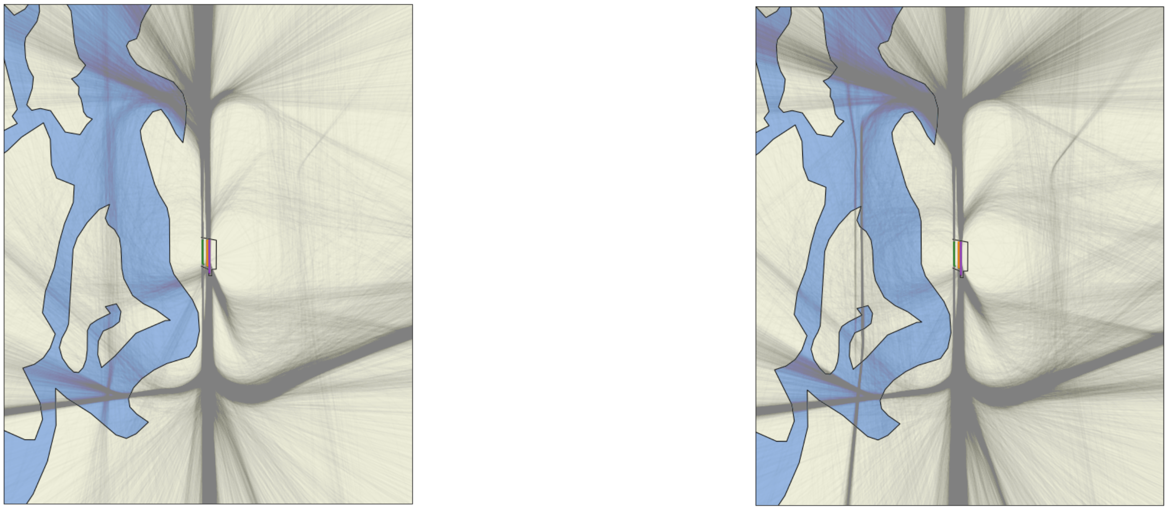
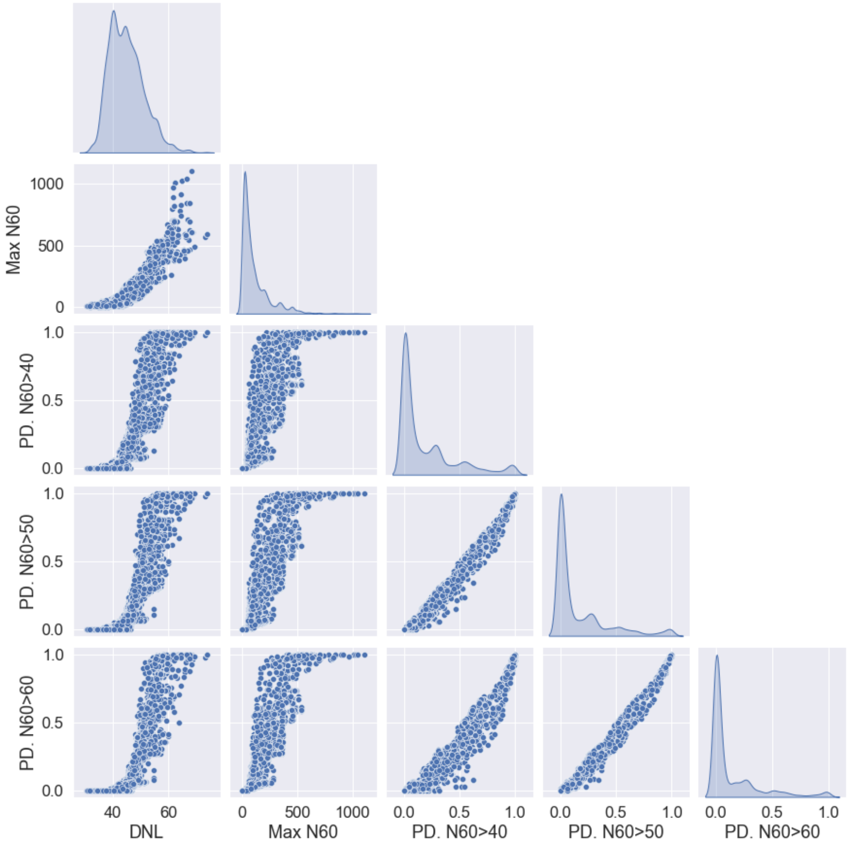
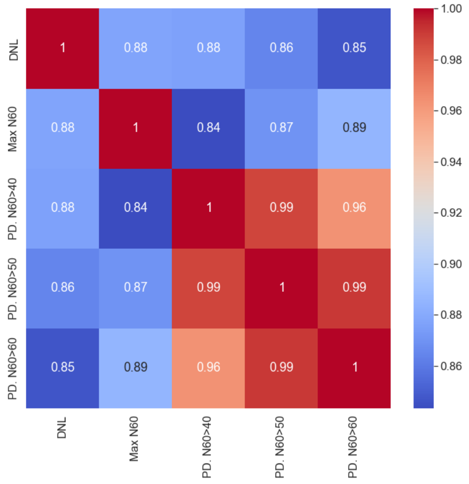


Figure A2: Correlation of Noise Metrics in Boston

(a) Pairplot



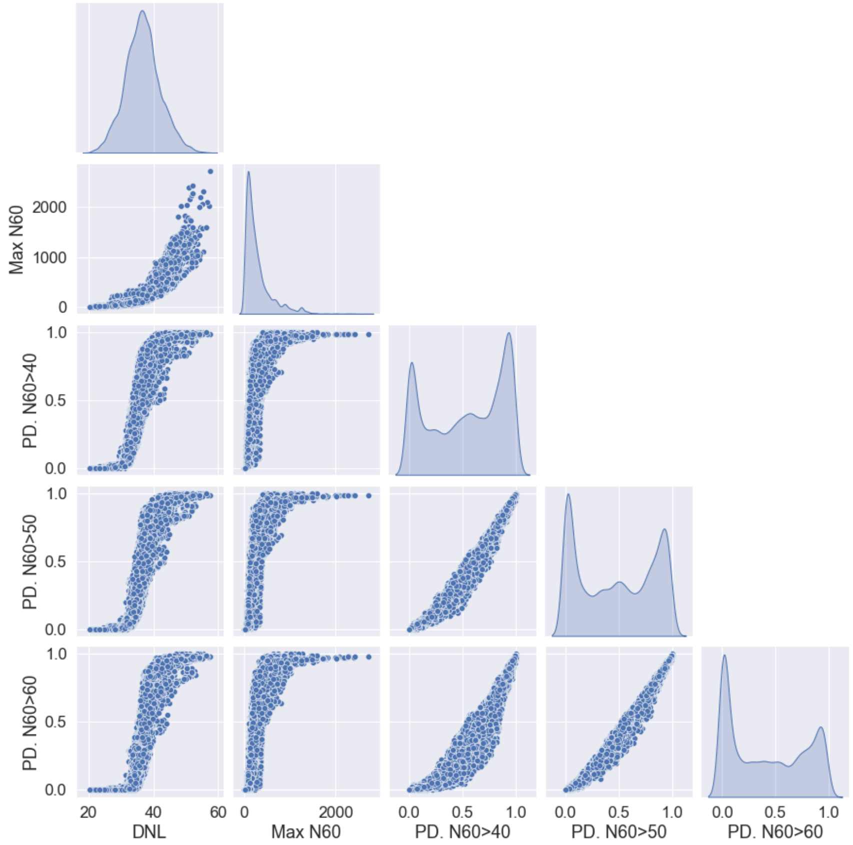
(b) Correlation Heatmap



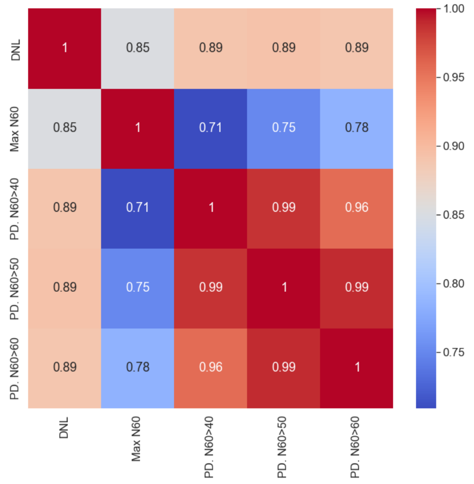
	DNL	Max N60	PD. N60>40	PD. N60>50	PD. N60>60
DNL	1	0.88	0.88	0.86	0.85
Max N60	0.88	1	0.84	0.87	0.89
PD. N60>40	0.88	0.84	1	0.99	0.96
PD. N60>50	0.86	0.87	0.99	1	0.99
PD. N60>60	0.85	0.89	0.96	0.99	1

Figure A3: Correlation Among Noise Metrics in Chicago

(a) Pairplot



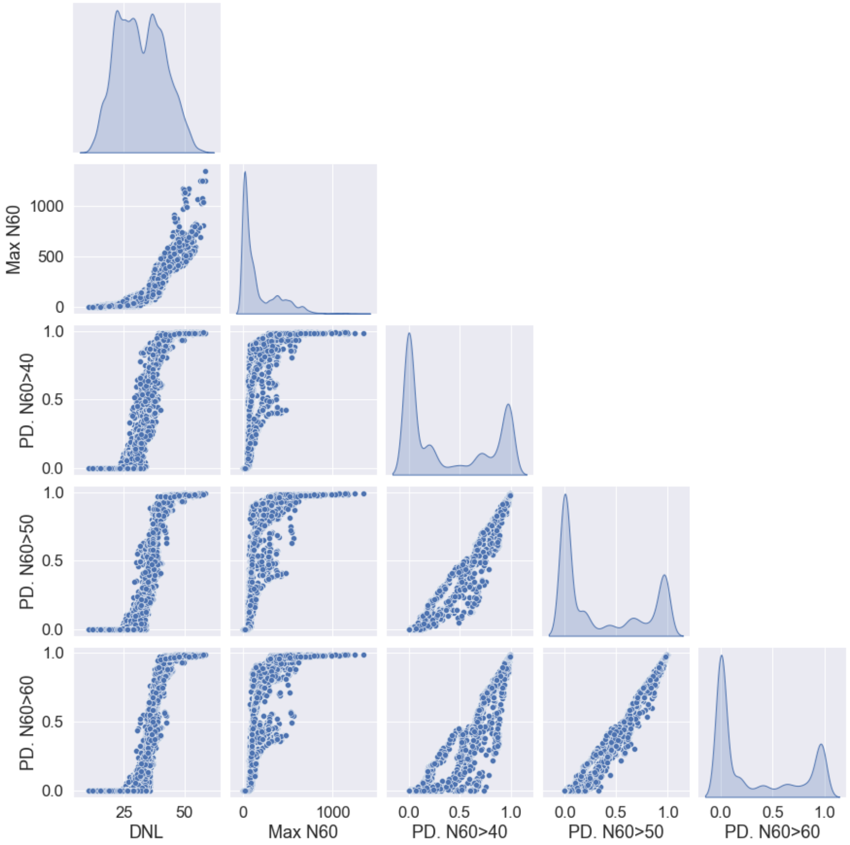
(b) Correlation Heatmap



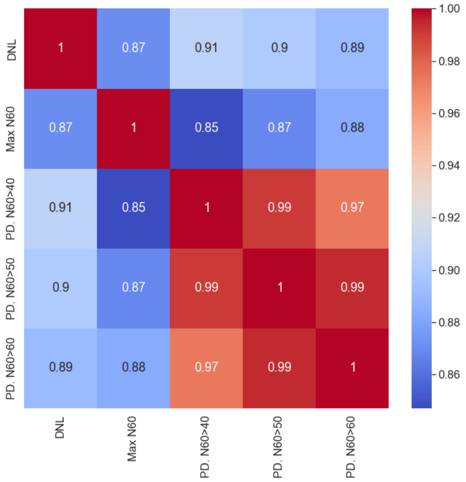
	DNL	Max N60	PD. N60>40	PD. N60>50	PD. N60>60
DNL	1	0.85	0.89	0.89	0.89
Max N60	0.85	1	0.71	0.75	0.78
PD. N60>40	0.89	0.71	1	0.99	0.96
PD. N60>50	0.89	0.75	0.99	1	0.99
PD. N60>60	0.89	0.78	0.96	0.99	1

Figure A4: Correlation Among Noise Metrics in Seattle

(a) Pairplot



(b) Correlation Heatmap



	DNL	Max N60	PD. N60>40	PD. N60>50	PD. N60>60
DNL	1	0.87	0.91	0.9	0.89
Max N60	0.87	1	0.85	0.87	0.88
PD. N60>40	0.91	0.85	1	0.99	0.97
PD. N60>50	0.9	0.87	0.99	1	0.99
PD. N60>60	0.89	0.88	0.97	0.99	1

Supplemental Appendix A.2 Data Details: Housing Transaction and Assessment Data

We restrict the transaction data in several ways. First, we collect transaction-level housing prices and characteristic data in three urban areas in 2011 and 2016. We focus on single- and multi-family residential properties within 20X20 nautical square miles of geospace around three airports. To restrict the sample to specific types of properties, we utilize information from both property land-use descriptions and standard codes. For example, for transactions that we cannot identify from the land-use descriptions, we use "RR101", "RR999", "RR000", and "RR102" in standard code to find single- and multi-family residential houses. We then follow Currie et al. (2015) and restrict our sample to homes that sold for above \$50,000 but below \$2M to remove the effect of outliers on our econometric results. Previous studies followed a similar strategy by eliminating very high-priced (above the 99th percentile) and low-priced (below the 1st percentile) homes to remove the effect of outliers on the econometric results.

Second, we restrict our sample to the fair market value transactions by ruling out arm's length transactions, intra-family transactions, transactions under distress (e.g., foreclosures), transactions below market value from public actors (e.g., by a targeted sale to veterans), and listed prices referring to monetary amounts other than the full property value (e.g., loans, mortgages, partial interests). Specifically, we exclude all the transactions with data type F, which are identified as foreclosures. We remove all the sales price amounts, standard type with "NA" to exclude all the potential arm's length transactions. Zillow data also provide an intra-family flag code that identifies intra-family and gift transfers. We remove any transactions with an indicator of the intra-family flag. We also remove all loan types classified as US Department of Veterans Affairs loans and state veteran loans to ensure the transaction prices are not below market value from public actors. We remove all partial interest transfer types with "M" to exclude all the potential listed prices. Lastly, we remove the least confident document codes for fair market value transactions by excluding the document types with "NFCM", "NTSL", "FCDE", and "LDCR".

Third, we drop properties that share the same transaction ID with other properties, were sold more than once within a calendar year, were sold more than five years before being built, or have missing sale prices. There are a few cases in which a transaction contains multiple houses after merging the transaction data with assessment data. We exclude these properties from our samples. Houses bought more than five years before being built or sold multiple times within a year are considered investments rather than intended for residential purposes. We remove these houses from our samples as well. Finally, we remove all transactions with missing sale prices.

Another issue about the Zillow transaction and assessment data (ZTRAX) is that some transactions have missing and inaccurate geo-locations. The ZTRAX latitude and longitude coordinates appear to have been derived using various geodesic datasets, but the information is not provided in the datasets. Nolte et al. (2021) selects several houses and matches the assessor parcel number between the transaction data and state parcel maps. They find most of the houses in our sample towards NAD83/WGS84. We conducted similar exercises, where we matched the assessor parcel numbers of homes in our samples with state parcel maps. We find the distance between the house geolocation under the WGS84 datum and the centroid of the parcel mostly within 140 meters, and a small number of properties were assigned to the wrong geo-locations. We first complement properties with missing geolocations from the assessment data and then use the GeoCoder API to improve the completeness of this location information in our samples. If we still have missing geolocations, we drop these transaction samples.

ZTRAX data contain a significant number of missing values for house attributes. For example, the size of the property is defined by several variables: “Living Building Area”(BAL), “Gross Building Area”(BAG), or “Total Building Area”(BAT). The “Living Building Area” is usually taken as the property area. However, only about 70% of arm’s length transactions have this information available in our selected areas. To supplement this information, we impute the missing value of the living building area by utilizing the information of other total area types. Specifically, we calculate the ratio of BAL to other total areas from available properties and fill in the missing value with other total areas adjusted by this ratio. Similarly, we impute the number of stories and bedrooms by accounting for the living area of the houses. For those observations that still have missing values, we fill them in with the median value of the variable in the sample. To address the outlier issue of house attributes, we also cut property characteristics: dropping properties with square footage $\geq$ 20,000, # bedrooms or bathrooms $\geq$ six, or # stories $\geq$ three.

To link noise grids with house addresses, for each 1/4-by-1/4 nautical square miles noise grid, we create the centroid of each noise grid and calculate the distance between each centroid to house addresses in our sample. We then find the nearest noise grid for a house address and assign its noise output to this house. Previous studies have attempted to use the kriging method to interpolate the value between centroids. Given the spatial resolution of our noise grids, we believe that the differences in noise outputs from different methods do not have significant impacts on our econometric results.

Supplemental Appendix A.3 Additional Evidence on Spatial FES and Housing Attributes

Table A1: Log of DNL Variance Explained by Sets of Fixed Effects (Adj. R^2)

	Zip-by-year FEs	Grid-by-year FEs	Tract-by-year FEs	Zip-by-year Time Trends	Grid-by-year Time Trends	Grid-by-year Time Trends
Without Block Group FEs						
Boston	.853	.942	.968	.792	.876	.902
Chicago	.908	.961	.978	.877	.925	.942
Seattle	.94	.982	.982	.939	.981	.98
With Block Group FEs						
Boston	.979	.987	.985	.937	.927	.985
Chicago	.985	.99	.99	.96	.958	.99
Seattle	.994	.996	.993	.993	.994	.993

Notes: Each column and row represents a separate regression. We regress the log of DNL on different sets of fixed effects and report the adjusted R^2. The bottom panel includes additional census-block-group fixed effects.

Table A2: Additional Summary Statistics for Housing, Noise, Neighborhoods

	Boston Logan			Chicago O'Hare			Seattle Tacoma		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Age	80.59	80.42	80.51	60.94	60.14	59.93	36.25	36.70	36.58
No Of Stories	2.06	2.05	2.04	1.49	1.49	1.49	1.58	1.56	1.57
Total Bath	2.43	2.38	2.38	1.78	1.79	1.79	1.99	2.00	2.01
Total Bedrooms	3.90	3.86	3.85	3.23	3.24	3.25	3.12	3.13	3.13
Lot Size (ft^2)	9853.56	9387.46	9340.25	7745.63	7796.98	7869.75	12347.06	11853.61	12005.99
Basement Dummy	0.44	0.44	0.45	0.03	0.03	0.03	0.30	0.31	0.31
Fireplace Dummy	.	.	.	.	.	.	0.40	0.40	0.40
Average Condition	0.60	0.61	0.61	.	.	.	0.36	0.37	0.36
Excellent Condition	0.04	0.03	0.03	.	.	.	0.01	0.01	0.01
Fair Condition	0.02	0.02	0.02	.	.	.	0.10	0.11	0.10
Pool Dummy	0.03	0.03	0.03	.	.	.	.	.	.
Block group median income ($K)	94.89	94.83	95.35	88.33	89.26	89.96	84.60	84.77	86.18
Block group under 18 (%)	19.03	19.06	19.04	21.62	21.59	21.65	19.04	19.01	18.87
Block group non-white (%)	24.37	23.63	23.22	26.52	25.06	24.66	37.69	37.74	37.45
City Hall	0.86	0.86	0.86	0.02	0.02	0.02	0.01	0.01	0.01
Road	0.31	0.31	0.31	0.22	0.22	0.21	0.16	0.16	0.16
Rail	0.17	0.17	0.17	0.15	0.15	0.15	0.03	0.03	0.03
Shopping Mall	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Open Space	0.11	0.10	0.10	0.04	0.03	0.03	0.09	0.09	0.09
Coastal Line	0.02	0.02	0.02	0.00	0.00	0.00	0.03	0.03	0.03
Observations	24854	23450	21989	37752	36302	33913	36336	34726	30136

Notes: This table reports additional summary statistics for the key variables included in the analysis for Boston Logan, Chicago O'Hare, and Seattle Tacoma Airports. Column (1) shows the statistics without trimming the sale prices and excluding houses with multiple transactions in a year; column (2) reports the statistics without excluding houses with multiple transactions in a year; column (3) depicts the final sample.

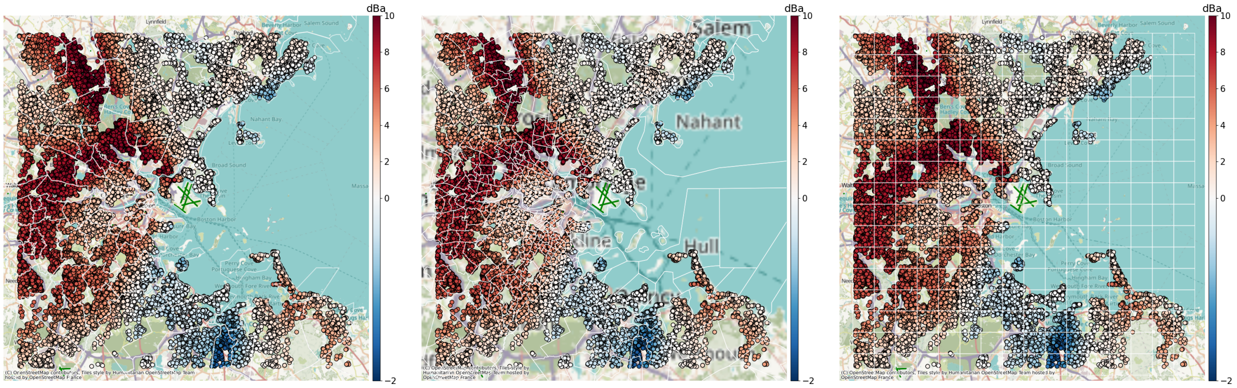
Supplemental Appendix A.4 Additional Evidence On Spatial Resolution of Three Localities

To better understand the plausible spatial scale, we conduct a series of analyses using different sets of spatial fixed effects across three localities. We consider three types of spatial resolution: zip code, census tract, and 2x2 mile grid. Figure A1 shows the scale of three resolutions with DNL changes over our study period in three localities. The average size of the zip code in the Boston sample is around 12 square miles, varying from 1.5 to 57 square miles. Chicago has a similar average size of 12 square miles, while the average size in Seattle is around 32 square miles. This is likely due to the lower population density in the Seattle area. In terms of census tracts, the average size in Boston and Chicago is around 2.6 square miles, while the average size in Seattle is 5 square miles. Given the quarter-by-quarter nautical square miles resolution in noise output, it is possible that little variation in airplane noise remains for small census tracts in Boston and Chicago after controlling for spatial fixed effects.

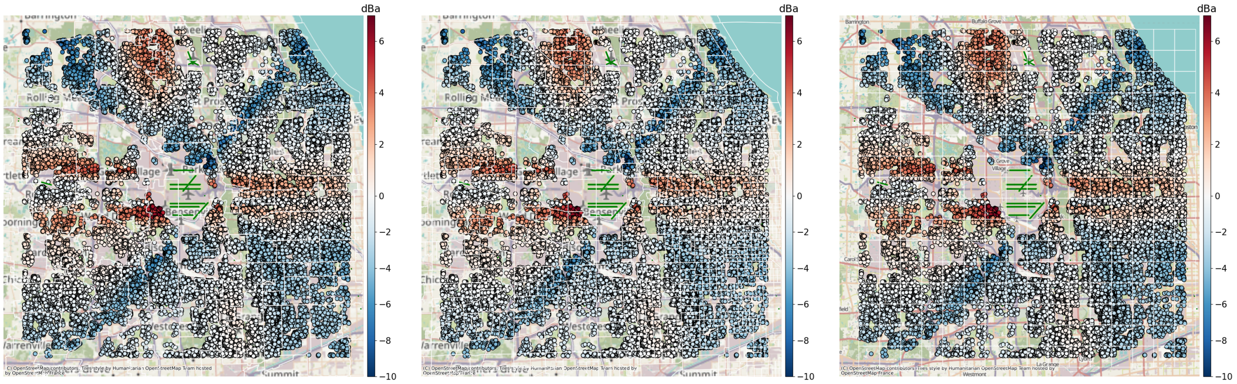
We plot the variation in noise measures after controlling for spatial fixed effects, the variation in housing prices, and the number of observations by three resolutions in Boston in Figure A6. The geographic areas were discarded if they contained fewer than 30 transactions in 2011 and 2016. In figure A6g-A6i, we find some evidence that using census tracts as the spatial resolution in Boston might be problematic, as no variation in airplane noise exposure remains in a significant number of areas after controlling for spatial fixed effects. In contrast, zip code and grid resolutions allow more variation and cover more geographic areas than census tract spatial resolution. Similarly, taking a closer look at Figure A7 in Chicago, we find the census tracts in urban areas were discarded due to the limited transactions for analysis. In contrast, zip code and grid resolutions provide better sample coverage and more variation in noise measures. For the Seattle sample, a closer look at Figure A8 suggests similar coverage of the sample and variation in noise measures across three resolutions. Therefore, using zip codes in Boston and Chicago and the census tracts in Seattle seems like a plausible spatial resolution to address the omitted variable bias in our setting.

Figure A5: DNL Changes with Geography Boundary

(a) Zip codes (Boston) (b) Census Tract (Boston) (c) 2x2 Mile Grid (Boston)



(d) Zip codes (Chicago) (e) Census Tract (Chicago) (f) 2x2 Mile Grid (Chicago)



(g) Zip codes (Seattle) (h) Census Tract (Seattle) (i) 2x2 Mile Grid (Seattle)

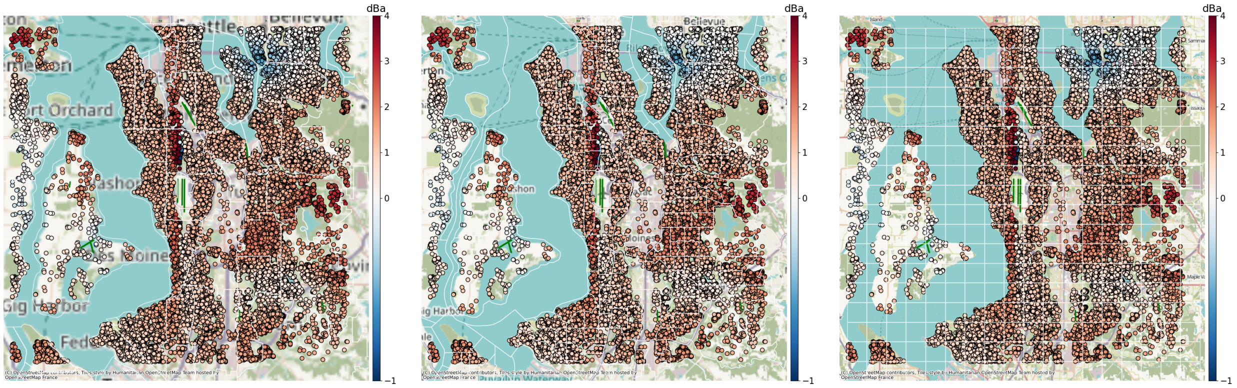
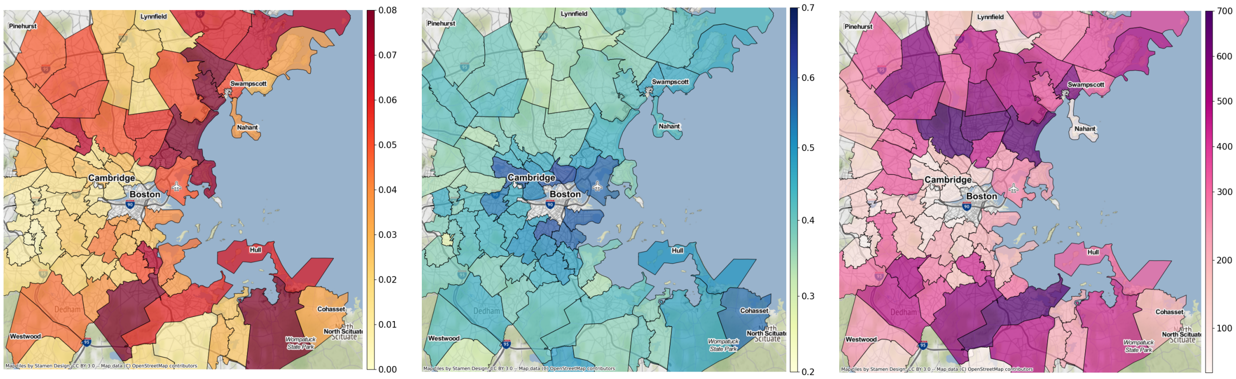
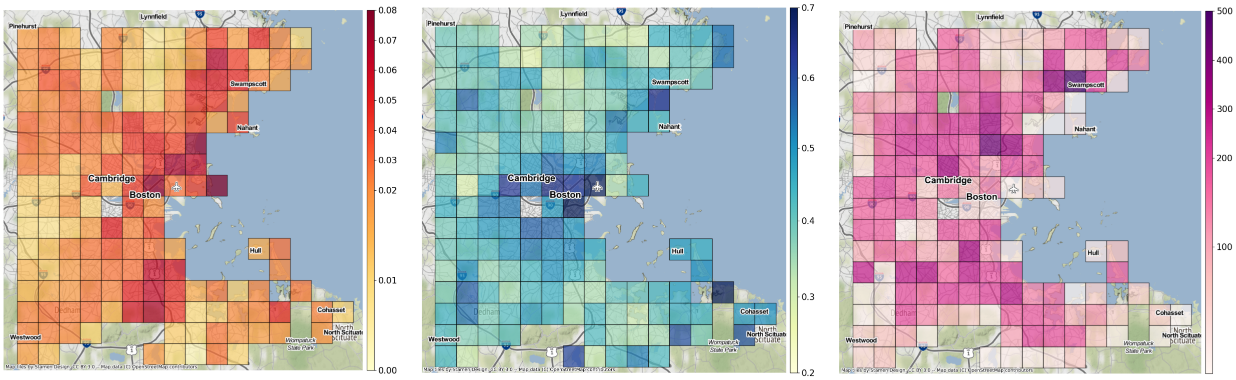


Figure A6: Within-Geography Variation in DNL, Property Prices, and Number of Observations in Boston

(a) DNL Variation (Zip) (b) Price Variation (Zip) (c) Observations (Zip)



(d) DNL Variation (Grid) (e) Price Variation (Grid) (f) Observations (Grid)



(g) DNL Variation (Tract) (h) Price Variation (Tract) (i) Observations (Tract)

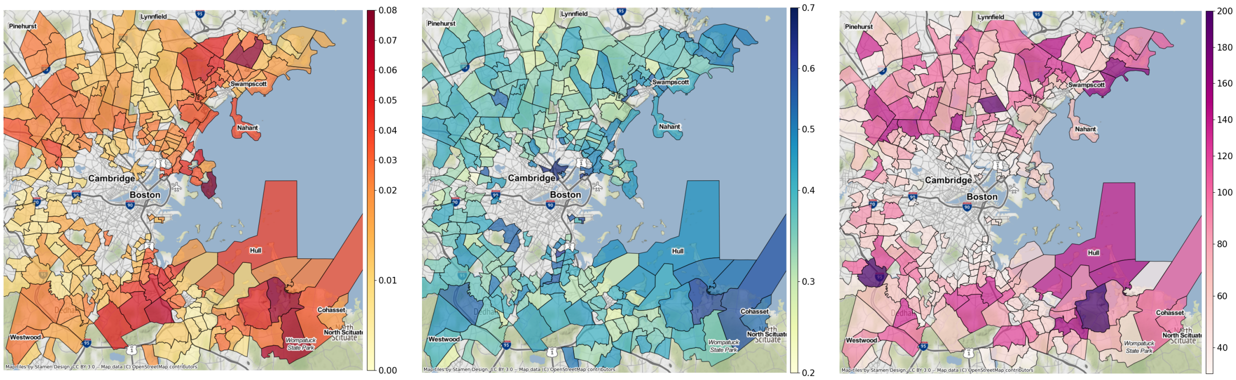
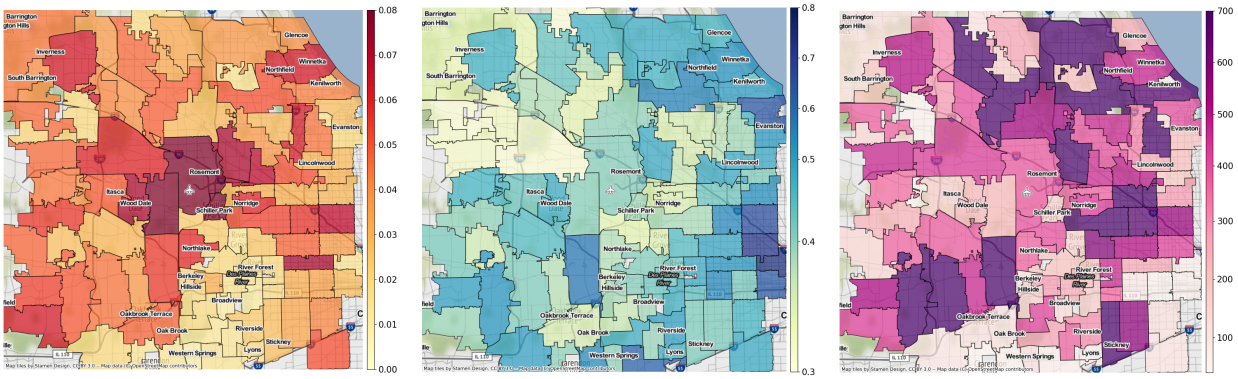
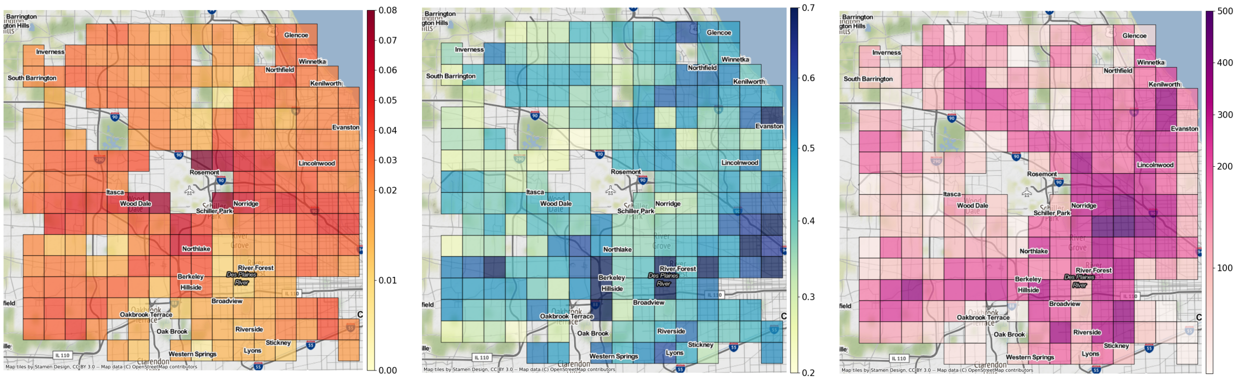


Figure A7: Within-Geography Variation in DNL, Property Prices, and Number of Observations in Chicago

(a) DNL Variation (Zip) (b) Price Variation (Zip) (c) Observations (Zip)



(d) DNL Variation (Grid) (e) Price Variation (Grid) (f) Observations (Grid)



(g) DNL Variation (Tract) (h) Price Variation (Tract) (i) Observations (Tract)

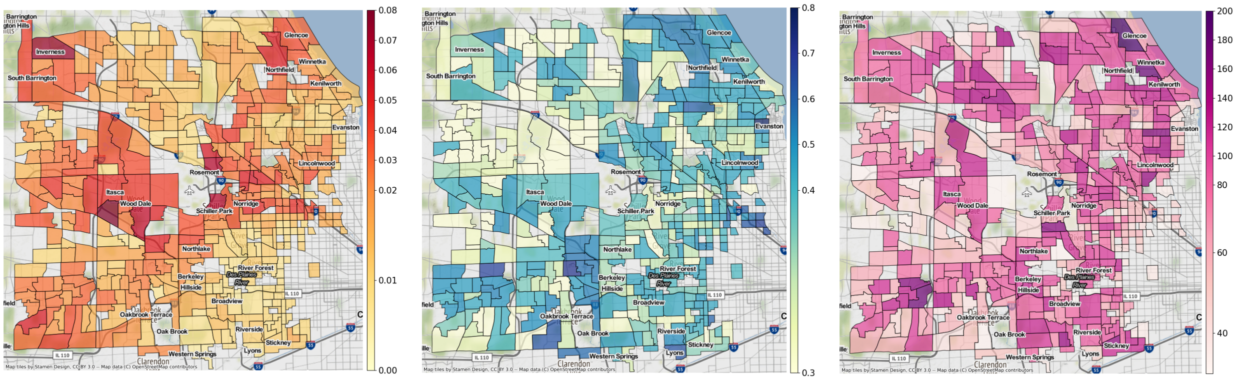
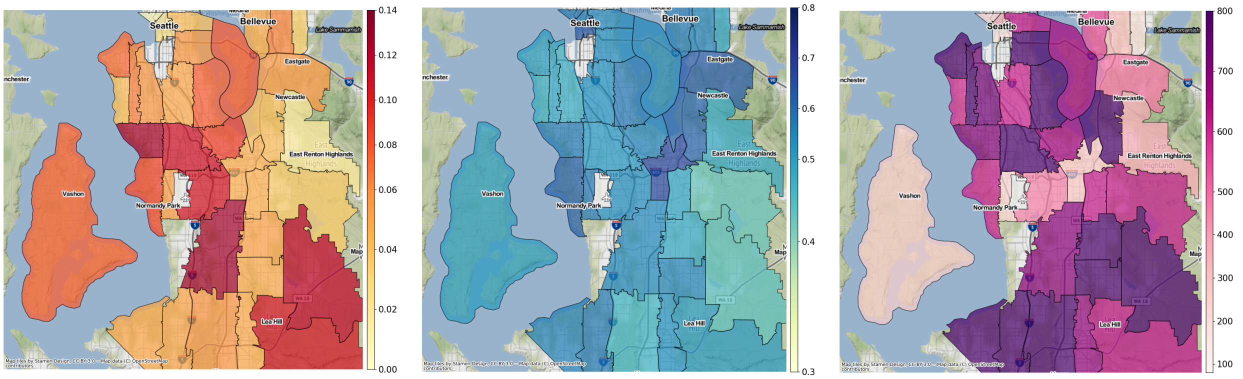
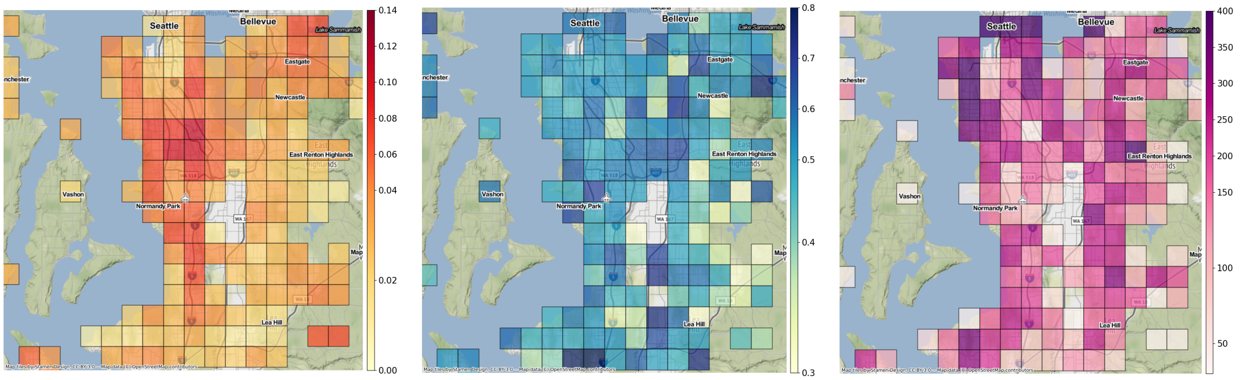


Figure A8: Within-Geography Variation in DNL, Property Prices, and Number of Observations in Seattle

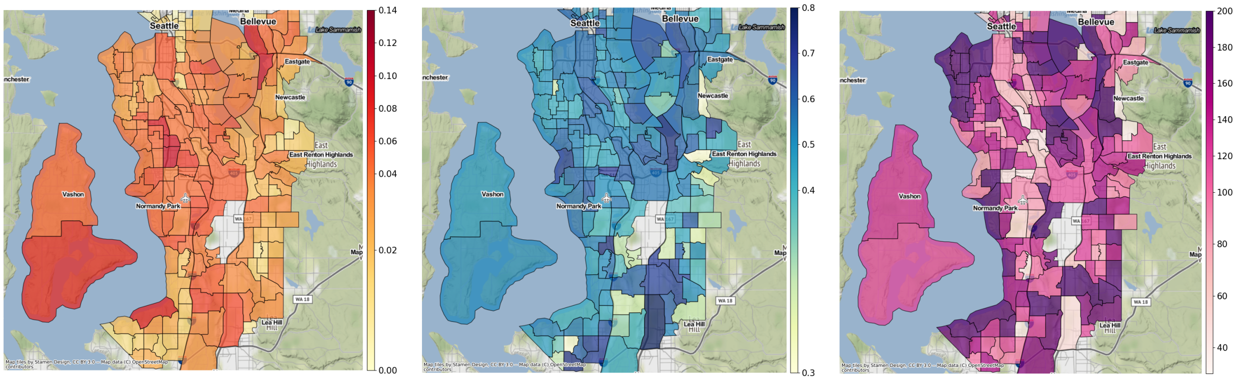
(a) DNL Variation (Zip) (b) Price Variation (Zip) (c) Observations (Zip)



(d) DNL Variation (Grid) (e) Price Variation (Grid) (f) Observations (Grid)



(g) DNL Variation (Tract) (h) Price Variation (Tract) (i) Observations (Tract)



Supplemental Appendix B Robustness Checks and Sensitivity Tests

Table B1: Robustness Checks: Alternative Function Forms

Function form	semi-log	log-log	Box-Cox transformation			
			lhs-only	rhs-only	both-same	both-diff
	(1)	(2)	(3)	(4)	(5)	(6)
Boston Logan Airport						
DNL	-0.004***		-0.060***	-5466.789	-0.518**	-0.957**
	(0.001)		(0.014)	(5887.310)	(0.050)	(0.578)
ln(DNL)		-0.262***				
		(0.048)				
θ			0.210***		0.192***	0.205***
			(0.012)		(0.007)	(0.010)
λ				0.241***	0.192***	0.055*
				(0.052)	(0.007)	(0.032)
Observations	20835	20835	20835	20835	20835	20835
Log likelihood	-267126	-262003	-262311	-266706	-261649	-261627
LR		10246	9630	840	10954	10998
Chicago O'Hare Airport						
DNL	-0.006***		-0.061***	-80.995***	-1.778***	-1.075***
	(0.001)		(0.001)	(3.831)	(0.117)	(0.035)
ln(DNL)		-0.224***				
		(0.044)				
θ			0.116***		0.118***	0.111***
			(0.006)		(0.006)	(0.006)
λ				2.035***	0.118***	0.231***
				(0.036)	(0.006)	(0.024)
Observations	33326	33326	33326	33326	33326	33326
Log likelihood	-425203	-413792	-413813	-424965	-413580	-413627
LR		22822	22780	476	23046	23152
Seattle Tacoma Airport						
DNL	-0.012***		-0.023***	-228.519***	-0.411***	-0.611***
	(0.002)		(0.000)	(17.773)	(0.079)	(0.051)
DNL^2		-0.299***				
		(0.062)				
θ			0.050***		0.030***	0.034***
			(0.006)		(0.006)	(0.007)
λ				1.865***	0.030***	-0.083**
				(0.093)	(0.006)	(0.028)
Observations	29882	29882	29882	29882	29882	29882
Log likelihood	-364322	-354258	-354520	-364306	-354247	-354239
LR		20056	19944	148	19970	19970

Notes: Column (1) uses a semi-log model, and column (2) uses a log-log model. We apply various restrictions to demonstrate the performance of the Box-Cox transformation. For instance, columns (3) and (4) permit transformations only on the left-hand side and right-hand side, respectively. Columns (5) and (6) allow transformations on both sides, with column (6) permitting different parameters for each side. The dependent variable is the property transaction prices in 2011 and 2016. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B2: DNL Impacts: Alternative Fixed Effects or Trends

	(1)	(2)	(3)	(4)	(5)	(6)
Boston Logan Airport						
ln(DNL)	-0.262*** (0.048)	-0.327*** (0.073)	-0.252** (0.102)	-0.251*** (0.040)	-0.217*** (0.050)	-0.086 (0.056)
Observations	20835	20831	20800	20837	20836	20819
Chicago O'Hare Airport						
ln(DNL)	-0.224*** (0.044)	-0.222*** (0.068)	0.152* (0.086)	-0.138*** (0.039)	-0.093* (0.050)	0.121** (0.055)
Observations	33326	33334	33267	33326	33338	33316
Seattle Tacoma Airport						
ln(DNL)	-0.179*** (0.037)	-0.520*** (0.063)	-0.299*** (0.062)	-0.184*** (0.036)	-0.457*** (0.060)	-0.260*** (0.059)
Observations	29472	29861	29882	29476	29878	29885
ZipXYear FEs	Yes					
GridXYear FEs		Yes				
TractXYear FEs			Yes			
ZipXYear Trends				Yes		
GridXYear Trends					Yes	
TractXYear Trends						Yes

Notes: The dependent variable is the log of property transaction prices in 2011 and 2016 in three localities. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. All specifications include month fixed effects, house and neighborhood characteristics controls, and distance to the nearest city hall, highway, railroad, shopping mall, coastal line, and open space. All regressions use Eicker-White standard errors. * p<0.10, ** p<0.05, *** p<0.01.

Table B3: Robustness Checks: Alternative Housing Samples

	1 Year	2 Years	3 Years	4 Years	5 Year
Boston Logan Airport					
ln(DNL)	-0.262*** (0.048)	-0.223*** (0.033)	-0.219*** (0.026)	-0.200*** (0.023)	-0.197*** (0.020)
Observations	20835	41850	62805	83249	103891
Chicago O'Hare Airport					
ln(DNL)	-0.224*** (0.044)	-0.202*** (0.031)	-0.182*** (0.025)	-0.200*** (0.021)	-0.226*** (0.018)
Observations	33326	66942	98917	130487	165398
Seattle Tacoma Airport					
ln(DNL)	-0.299*** (0.062)	-0.256*** (0.044)	-0.262*** (0.036)	-0.295*** (0.031)	-0.288*** (0.027)
Observations	29882	59376	85629	112565	147864

Notes: The dependent variable is the log of property transaction prices in 2011 and 2016. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. In the three localities, we extended our samples by multiple years (1-5 years) before 2011 and after 2016. All specifications include month fixed effects, house and neighborhood characteristics controls, distance to the nearest city hall, highway, railroad, shopping mall, coastal line, open space, and spatial FEs. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B4: Robustness Checks: Alternative Sales Price Bounds

	(1)	(2)	(3)	(4)	(5)
Boston Logan Airport					
ln(DNL)	-0.262***	-0.248***	-0.260***	-0.246***	-0.241***
	(0.048)	(0.046)	(0.045)	(0.043)	(0.043)
Observations	20835	20734	20766	20497	20323
Chicago O'Hare Airport					
ln(DNL)	-0.224***	-0.213***	-0.213***	-0.192***	-0.183***
	(0.044)	(0.043)	(0.042)	(0.041)	(0.041)
Observations	33326	32936	32539	32052	31594
Seattle Tacoma Airport					
ln(DNL)	-0.299***	-0.306***	-0.313***	-0.275***	-0.256***
	(0.062)	(0.060)	(0.059)	(0.058)	(0.056)
Observations	29882	29692	29442	29185	28838
Lower Bound	50K	60K	70K	80K	90K
Upper Bound	2M	1.9M	1.8M	1.7M	1.6M

Notes: The dependent variable is the log of property transaction prices in 2011 and 2016. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. All specifications include month fixed effects, house and neighborhood characteristics controls, distance to the nearest city hall, highway, railroad, shopping mall, coastal line, open space, and spatial FEs. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B5: Robustness Checks: Clustered at fixed effects level

	Boston	Chicago	Seattle
ln(DNL)	-0.246** (0.090)	-0.238* (0.110)	-0.291** (0.106)
Observations	20755	33214	29748

Notes: The dependent variable is the log of property transaction prices in 2011 and 2016. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. All specifications include month fixed effects, house and neighborhood characteristics controls, distance to the nearest city hall, highway, railroad, shopping mall, coastal line, open space, and spatial FEs. Standard errors are clustered at the fixed effects level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B6: Heterogeneous effects of DNL across different housing price quantiles

	(1)q25	(2)q50	(3)q75
Boston Logan Airport			
ln(DNL)	-0.266*** (0.091)	-0.109 (0.070)	-0.132 (0.122)
Observations	20,835	20,835	20,835
Chicago O'Hare Airport			
ln(DNL)	-0.111 (0.115)	-0.068 (0.075)	-0.140* (0.073)
Observations	33,326	33,326	33,326
Seattle Tacoma Airport			
ln(DNL)	-0.383*** (0.111)	-0.278*** (0.081)	-0.126 (0.129)
Observations	29,882	29,882	29,882
House Characteristics	Yes	Yes	Yes
Distance Index	Yes	Yes	Yes
Neighborhood	Yes	Yes	Yes

Notes: We conduct quantile regressions at the housing price distribution's 25th, 50th, and 75th percentiles to examine how the effects vary across different price levels. The dependent variable is the log of property transaction prices in 2011 and 2016. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. All specifications include month fixed effects, house and neighborhood characteristics controls, distance to the nearest city hall, highway, railroad, shopping mall, coastal line, open space, and Zip(Tract)-by-year fixed effects. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B7: DNL Impacts across different airplane noise intervals

	Boston Logan Airport		Chicago O'hare Airport		Seattle Tacoma Airport	
	(1)	(2)	(3)	(4)	(5)	(6)
ln(DNL)	-0.269***		-0.220***		-0.282***	
	(0.048)		(0.044)		(0.063)	
X I{Noise $\leq 40dB$}		-0.114		-0.068		-0.166**
		(0.101)		(0.059)		(0.073)
X I{Noise $\in (40dB, 50dB]$}		-0.218***		-0.299***		-0.590***
		(0.076)		(0.075)		(0.192)
X I{Noise $>$ *50dB*}		-0.262**		-0.011		-1.201
		(0.131)		(0.294)		(0.741)
I{Noise $\in (40dB, 50dB]$}		0.370		0.820**		1.572**
		(0.400)		(0.323)		(0.767)
I{Noise $>$ *50dB*}		0.530		-0.312		3.951
		(0.641)		(1.168)		(2.949)
Observations	20835	20835	33326	33326	29882	29882
R-sq	.644	.644	.675	.675	.543	.543
AIC	14069.6	14073.1	26745.4	26733.3	33380.8	33373.2
BIC	14204.6	14239.8	26888.4	26910	33521.9	33547.5

Notes: We employ a piece-wise linear specification to allow for non-constant marginal effects across the range of airplane noise exposure. The airplane noise variable is segmented into three intervals: $\{[\text{min} - 40), (40 - 50], (50 - \text{max}]\}$ dB. We interact the log of noise with these intervals to determine if the elasticities vary among them. The dependent variable is the log of property transaction prices in Illinois in 2011 and 2016. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. The dataset was min-max normalized before any analysis to deal with the different units and orders of magnitude. All specifications include month fixed effects, house and neighborhood characteristics controls, distance to the nearest city hall, highway, railroad, shopping mall, coastal line, open space, and Zip(Tract)-by-year fixed effects. All regressions use Eicker-White standard errors. * p<0.10, ** p<0.05, *** p<0.01.

Supplemental Appendix C Additional Findings

Supplemental Appendix C.1 Alternative Noise Metrics

Table C1: Impacts of Alternative Noise Metrics, Boston Logan Airport

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(DNL)	-0.227***					-0.213**	-0.223**	-0.194**
	(0.042)					(0.097)	(0.097)	(0.097)
ln(MaxN60)		-0.137***				-0.107	-0.076	0.001
		(0.027)				(0.073)	(0.072)	(0.072)
ln(%D(N60>40))			-0.032**			0.068***		
			(0.015)			(0.024)		
ln(%D(N60>50))				-0.043***			0.048**	
				(0.015)			(0.024)	
ln(%D(N60>60))					-0.065***			-0.016
					(0.014)			(0.023)
Observations	20835	20835	20835	20835	20835	20835	20835	20835
AIC	13314.82	13320.01	13342.14	13337.74	13324.35	13310.04	13314.61	13318.22
BIC	13489.60	13494.79	13516.91	13512.52	13499.13	13500.71	13505.28	13508.89

Notes: The dependent variable is the log of property transaction prices in 2011 and 2016 in Massachusetts. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. DNL, MaxN60, and %D(N60>40/50/60) represent average noise level, the number of noise events above 60 dBA at the peak day, and the percentage of days having the number of noise events above 60 dBA more than 40/50/60 times, respectively. The dataset was min-max normalized before any analysis to deal with the different units and orders of magnitude. All specifications include month fixed effects, house and neighborhood characteristics controls, distance to the nearest city hall, highway, railroad, shopping mall, coastal line, open space, and Zip-by-year fixed effects. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table C2: Impacts of Alternative Noise Metrics, Chicago O'Hare Airport

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(DNL)	-0.235***					-0.139*	-0.221***	-0.291***
	(0.046)					(0.079)	(0.079)	(0.079)
ln(MaxN60)		-0.179***				-0.080	-0.120*	-0.178***
		(0.038)				(0.063)	(0.063)	(0.064)
ln(%D(N60>40))			-0.079***			-0.009		
			(0.022)			(0.029)		
ln(%D(N60>50))				-0.029			0.068***	
				(0.020)			(0.026)	
ln(%D(N60>60))					0.003			0.029***
					(0.004)			(0.005)
Observations	33326	33326	33326	33326	33326	33326	33326	33326
AIC	26899.65	26901.37	26911.73	26923.28	26925.12	26901.75	26894.49	26867.72
BIC	27042.69	27044.41	27054.77	27066.31	27068.16	27061.62	27054.36	27027.59

Notes: The dependent variable is the log of property transaction prices in 2011 and 2016 in Illinois. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. DNL, MaxN60, and %D(N60>40/50/60) represent average noise level, the number of noise events above 60 dBA at the peak day, and the percentage of days having the number of noise events above 60 dBA more than 40/50/60 times, respectively. The dataset was min-max normalized before any analysis to deal with the different units and orders of magnitude. All specifications include month fixed effects, house and neighborhood characteristics controls, distance to the nearest city hall, highway, railroad, shopping mall, coastal line, open space, and Zip-by-year fixed effects. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table C3: Impacts of Alternative Noise Metrics, Seattle Tacoma Airport

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(DNL)	-0.300***					-0.426***	-0.430***	-0.433***
	(0.062)					(0.089)	(0.089)	(0.089)
ln(MaxN60)		-0.022**				0.025	0.022	0.020
		(0.010)				(0.015)	(0.015)	(0.015)
ln(%D(N60>40))			-0.003			0.002		
			(0.004)			(0.004)		
ln(%D(N60>50))				-0.001			0.005	
				(0.004)			(0.005)	
ln(%D(N60>60))					0.000			0.007
					(0.004)			(0.004)
Observations	29882	29882	29882	29882	29882	29882	29882	29882
AIC	33216.79	33237.90	33242.52	33243.38	33243.51	33216.46	33215.25	33213.69
BIC	33382.89	33404.00	33408.62	33409.48	33409.61	33399.17	33397.96	33396.40

Notes: The dependent variable is the log of property transaction prices in 2011 and 2016 in Seattle. All prices are deflated to 2011 dollars using the US Bureau of Labor Statistics Consumer Price Index. DNL, MaxN60, and %D(N60>40/50/60) represent average noise level, the number of noise events above 60 dBA at the peak day, and the percentage of days having the number of noise events above 60 dBA more than 40/50/60 times, respectively. The dataset was min-max normalized before any analysis to deal with the different units and orders of magnitude. All specifications include month fixed effects, house and neighborhood characteristics controls, distance to the nearest city hall, highway, railroad, shopping mall, coastal line, open space, and Zip-by-year fixed effects. All regressions use Eicker-White standard errors. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

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