Valuing Noise Pollution in a Residential Sorting Model: Evidence from Flight Path Changes in Phoenix, Arizona

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Abstract

Noise pollution from airplanes can reduce property values by creating a disamenity for residents. I estimate the effect of noise pollution on residential properties in the Phoenix metropolitan area, Arizona, using the quasi-random variation in flight routes. I used two changes in the noise exposure: computer-generated optimized flight path and reversal after the court's intervention. I developed the residential sorting model with heterogeneous preferences. The identification of these preferences on the spatial and temporal variation. My model estimates that the mean MWTP to avoid noise pollution is \$ 4,755. I also find that the heterogeneity in preference and MWTP to avoid noise pollution could vary from \$3,000 to \$7,000 with older and higher-income households having a higher WTP to avoid noise pollution. I relax the assumption on time-variant unobserved quality and find that ignoring this assumption overestimates the MWTP by 100%.

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One of the earliest documented noise regulations dates back to 44 BC when the senate of Julius Caesar passed the bill that wagons could no longer traverse suburban streets "before the tenth hour of the day (4 pm)" Vox (2018). More than two millennia later, we have come to recognize that noise pollution extends far beyond being a mere public nuisance. It is associated with a range of detrimental outcomes, including adverse health effects (Barregard et al., 2009), increased crime rates (Hener, 2022), and diminished property values (Von Graevenitz, 2018). However, isolating exogenous sources of variation in noise pollution has proven to be challenge. In this study, I surmount this challenge by leveraging two quasi-random alterations in airline flight paths to establish a causal link between airplane noise and property values.

Noise pollution has a profound impact on human health, disrupting sleep patterns (Sklarz and Miller), elevating the risk of hypertension (Barregard et al., 2009), and even increasing the incidence of strokes (Sørensen et al., 2011). Remarkably, airplane noise levels can reach up to 75 dB, equivalent to the noise produced by a vacuum cleaner, even at a distance of 5 miles from the airport. Historically, communities have often expressed distress over noise pollution stemming from the aviation industry, leading to protests, awareness campaigns, and legal actions against excessive noise exposure. For instance, homeowners filed a lawsuit against the Raleigh-Durham Airport Authority due to a sudden surge in airplane traffic, resulting in a substantial $1.8 million settlement in 1992 (Pope, 2008). Property prices, in turn, bear the imprint of noise pollution's disamenity, driven by concerns related to health, sleep disturbances, and overall annoyance. Buyers' decisions in the housing market, when presented with a spectrum of price-attribute-amenity bundles, can unveil their valuation of these amenities (Bishop et al., 2020).

The Federation of Aviation Administration (FAA) establishes flight routes throughout the United States. They introduced NextGen, a program that included the implementation of RNAV, a satellite-based navigation system at Phoenix Sky Harbor Airport (PHX airport), on September 18, 2014. This led to shorter, narrower, and more efficient flight routes, saving an estimated \$4.5 million annually in fuel and reducing carbon emissions. Without receiving any prior notice, Phoenix residents faced a change in their noise exposure because of the new computer-generated flight routes. The PHX airport witnessed a 30 times increase in the number of households complaining within one year of the policy. Complaints increased by over 100,000 in 2017. In response, historic Phoenix neighborhoods and the City of Phoenix administration filed a lawsuit against the FAA in June 2015. The court ruled in favor of the plaintiffs in August 2017, resulting in a partial policy reversal in March 2018, particularly impacting westward departures, which were aligned more closely with traditional flight paths, but remained narrower.

I rely on three main datasets: flight paths, housing data, and demographic data. The flight path dataset contains accurate information about the path taken by approximately 900,000 flights spread over a decade during three different policy regimes: conventional, NextGen, and partial reversal. Housing data includes information on property characteristics, location, and transactions for residential properties in Maricopa County, which consists of cities in the Phoenix metropolitan area. To supplement this information, I also use additional demographics like age and income data, which come from two different sources. I obtain the neighborhood attributes data at the block group level from ACS, and I use individual demography data from DataAxle.

The GIS flight path data was utilized with the FAA's Aviation Environmental Design Tool (AEDT) to calculate ground-level noise exposure. This process involved assigning the day-night average noise level (DNL), a measure of noise pollution, at the property level for each of the three phases.

For my analysis, I employed hedonic pooled cross-section and property-level fixed-effects models. The model's identification relies on the assumption of quasirandom variation resulting from the policy changes. To mitigate concerns of omitted variable bias, I leveraged the presence of many properties that appeared multiple times in my data set due to repeat sales. This allowed me to compare the same property sold under different noise exposure conditions, providing a robust approach to address potential bias.

The impact of the two policies resulted in significant changes in noise pollution exceeding 3 dB at certain locations, classifying them as inframarginal changes. Such substantial changes in amenities tend to trigger residential resorting within the region. To analyze this resorting phenomenon under changes in noise pollution, I developed a residential sorting model that incorporates heterogeneous preferences. This model extends the work of Bayer et al. (2007). Although existing residential sorting models rely primarily on spatial variation, my approach incorporates both spatial and temporal variations to identify model parameters. To address potential concerns related to time-invariant unobserved quality that might bias price coefficients, I employed property-type fixed effects. Additionally, to mitigate issues arising from unobserved quality that vary over time, I introduced instrumental variables (IVs) based on changes in property supply. These IVs provide a more robust framework to address such concerns.

I applied the residential sorting model to assess the welfare impact of a policy that alters the exposure to noise. The welfare change quantifies the expected compensating variation for each individual due to changes in their choice sets. I examined this welfare change in both partial equilibrium and general equilibrium contexts. The distinction lies in allowing prices to adapt to changes in noise exposure across the city within the general equilibrium framework. I decompose welfare measures into three components: (1) a money-metric measure of the utility change at each household's current residence, (2) the equilibrium capitalization of the policy change into prices at that residence, and (3) the value to the household of being able to sort across the transformed landscape, i.e. welfare because of the change in the choice sets. I estimate the welfare change for the owners and renters.

The results highlight a significant negative impact of airplane noise exposure on property values. In my reduced form specification, a 1 dB increase in noise exposure led to property value reductions ranging from 1.04% to 1.58%, depending on the specification. My preferred specification, which includes fixed effects at property level, estimated the effect at 1. 04%, equivalent to \$3,400. The estimate of my model of the mean Marginal Willingness to Pay (MWTP) to avoid noise pollution stands at \$ 4,755, slightly higher than my reduced form estimates. Furthermore, I observed heterogeneity in preferences and MWTP for noise pollution, ranging from \$3,000 to \$7,000, with older and higher income households showing greater willingness to pay to avoid noise pollution.

I have also observed that neglecting temporal variation and unobserved quality in time leads to an overestimation of the mean MWTP by almost 100%. Therefore, it is crucial to incorporate time-varying instrumental variables (IV) and to rely on temporal variation for identification whenever possible. The mean welfare gain per household is estimated at \$3,796 under the PE framework and \$98 under the GE framework. This substantial difference in welfare gains arises because prices increase in neighborhoods where noise pollution decreases, and vice versa. These price adjustments significantly reduce the expected welfare gain. Using the new equilibrium prices within the GE framework, I find that properties experiencing reduced noise pollution witness an increase of \$8,468 in property prices. Although NextGen's impact primarily affects 23% of properties with altered noise exposure, the price dynamics extend to all properties. The influence of policy changes the choices and housing decisions of residents, leading to a mean decline of \$99 in property prices for those unaffected by changes in noise pollution.

This paper contributes to the literature in multiple ways, which I group into three categories. The first set of contributions is related to my main findings of the reduced-form evidence. In practice, hedonic price functions have proven difficult to estimate because the amenity of interest is typically not randomly distributed between locations (Davis, 2004). This paper improves on the previous literature by disentangling the endogeneity between noise pollution and property prices using an unexpected quasirandom change in the flight paths generated by the computer. Furthermore, using the repeated sales data enables me to address omitted variable bias concerns as I compare the same property sold under different noise exposures. I find that the estimates from the cross-sectional specification are downward biased by 50%.

The second set of contributions relates to the novelty of the data. In terms of data, to the best of my knowledge, it is the first paper to use GIS flight path data to estimate the effect on the housing market by assigning noise pollution at the property level. Most of the literature on airplane noise has used noise contours which are discretized intervals that might introduce omitted variable bias through measurement error. Some papers limit the analysis to the properties located at the contours' borders, thus reducing the sample size. Using the flight paths and AEDT software enables me to test robustness with multiple measures of noise pollution such as SEL, and TALA.

The third contribution of this paper lies in the development of a residential sorting model. While Bayer et al. (2007) has been widely cited and replicated, the identification in these studies mainly relies on spatial amenity variation. In contrast, my paper leverages both spatial and temporal variations in the amenity, making it, to the best of my knowledge, the first to relax the assumption of time-varying unobserved quality within the housing market. The novelty of this paper is the development of instrumental variables (IVs) to address concerns related to the correlation between price changes and time-varying unobserved quality. My findings reveal that ignoring this factor results in an overestimation of the mean Marginal Willingness to Pay (MWTP) by more than 100%.

The remainder of the paper is organized as follows. Section 1 discusses the existing literature. Section 2 provides the background of the changes in the flight route. Section 3 describes data, and estimates of noise exposures, and presents summary statistics. Section 4 provides reduced-form evidence. Section 5 explains the model deployment. Section 6 presents the results, and Section 7 explains the welfare analysis.

1 Literature Review

Rosen (1974) seminal paper laid the theoretical foundations for the hedonic model. Since the 1970, this model has found applications across various fields. Urban economics, in particular, has extensively explored non-market amenities. A rich body of literature focuses on location-specific amenities, such as air quality (Chay and Greenstone, 2005), noise pollution (Pope, 2008), and water as an urban club good (Abbott and Klaiber (2011b)). The hedonic method has evolved significantly in its econometric implementation, particularly in terms of functional form selection and robustness to omitted variables Abbott and Klaiber (2011a).

The Noise Sensitivity Depreciation Index (NSDI) stands out as one of the most widely used indicators for quantifying the impact of noise on real estate prices Szczepańska et al. (2015). NSDI measures the percentage decrease in property value resulting from a 1 dB increase in noise exposure. Much of the existing literature on the effects of noise pollution on the housing market employs hedonic regression techniques, capturing the impact of various sources of noise pollution like airplaines and road traffic. As noise levels are typically measured in decibels (dB), the results are comparable across different sources of noise pollution. Some noteworthy findings include Von Graevenitz (2018), who report NSDI values ranging from 0.1% to 1.4% for noise levels exceeding 55 dB. Bateman et al. (2001), drawing from 18 studies, suggest that a 1 dB increase in aircraft noise results in a 0.64% reduction in property value. In Shelby County, Tennessee, Ozdenerol et al. (2015) find that traffic nuisance significantly negatively impacts housing values. Further insights come from Brandt and Maennig (2011) and Wilhelmsson (2000), who measure NSDI at 0.23% and 0.6% in Hamburg, Germany, and Sweden, respectively.

In recent years, significant progress has been made in empirical strategies. Numerous studies have demonstarted that the omitted variables can be of first-order importance Kuminoff et al. (2013). In my research, I address endogeneity concerns by leveraging quasi-random variation in noise exposure. Studies like Boes and Nüesch (2011), Cohen and Coughlin (2009), and Cohen et al. (2021) use variations in flight paths or airport closures as sources of quasi-random noise pollution variation. For instance, Cohen et al. (2021) investigates the immediate and long-term impact of airport closure in Denver on the nearby housing market. As proximity positively correlates with housing prices Lipscomb (2003), it is difficult to disentagle the effect purily because of noise pollution upon airport closure. My estimates are only because of the change in the noise pollution distinguishing my research from Cohen et al. (2021). Another approach, as used by Cohen and Coughlin (2009), involves analyzing variations in noise contours between 1990 and 2003 at Atlanta's airport. Noise exposure changes are spread over a decade, reflecting the adoption of quieter airplanes by commercial airlines. In contrast, my research focuses on a sudden and significant change in noise exposure caused by a computer-generated optimized flight path. While my approach shares similarities with Boes and Nüesch (2011), particularly in terms of data and empirical methodology, there are substantial differences. Notably, Boes and Nüesch (2011) concentrates on the residential rental market and employs a smaller dataset of 436 observations, whereas my study encompasses thousands of repeat sale property transactions. I use two quasi-random flight path changes. Boes and Nüesch (2011) also emphasize on the concern of omitted variable bias and find that the noise discounts are overestimated in cross-sectional studies because aircraft noise tends to be negatively correlated with omitted neighborhood and housing amenities.

Over the past decade, advances in economic models of sorting process have led to a new framework that promises to alter the ways we conceptualize the policy evaluation process in the future Kuminoff et al. (2013). These "equilibrium sorting" models use the properties of market equilibria, together with information on household behavior, to infer structural parameters that characterize preference heterogeneity. Some of the studies have used the quasi-random variation in the amenities in the model for identitication. Bayer et al. (2007) used RDD and Galiani et al. (2015) used RCT. Bayer et al. (2009) used the temporal variation and IVs to overcome the endogeniety bias concerns because of correlation between amenity levels and local unobserved attributes. They try to overcome the cencernsdue to the correlation between property prices and unobserved quality by moving price on the left-hand side of the regression equation. I overcome this concern by developing time-varying

IV that are likely to be correlated with the change in the property price and not with the time-variant unobserved quality.

2 Background

The Federation of Aviation Administration is responsible for deciding flight paths across the USA. The top panel of figure 1 shows the departure flight paths for a week during the conventional flight path phase (before September 18^{th}, 2014) at the Phoenix Skyharbor Airport. A red line represents each flight path. Airplanes departures and arrivals can happen in either eastward or westward directions. Departure and arrival direction depends on the wind direction. As the wind direction is eastward before noon, all departures and arrivals are eastward before noon and westward in the afternoon. Airplanes departing in the opposite direction of their destination have to turnover. For example, airplanes destined for Chicago and departing westward have to turn around and fly over the north of Phoenix.

FAA adopted NextGen, a portfolio of policies encompassing the planning and implementation of innovative new technologies and airspace procedures. Under the NextGen project, FAA adopted Random Area Navigation (RNAV), a method to instrument flight rules navigation that allows an aircraft to choose any course within a network of navigation beacons rather than navigate directly to and from the beacons. It also ensured a satellite-based navigation system and computer-generated optimized flight path. The objective was to conserve flight distance, reduce congestion, and allow flights into airports without beacons (reduce human error). It was expected to save \$3.6 million/ year in fuel burn and 4,300 metric tons on CO_2 emissions, which can be valued at approximately \$1 million Report (2016). The optimized flight paths generated by the computer under NextGen make the routes shorter and more concentrated. This is evident from the panel A of figure 1, which lays out the flight paths during a week of conventional and NextGen phases. Conventional flight paths are represented by red and NextGen flight paths by blue.

The NextGen flight paths introduced noise pollution in newer areas and changed the city's noise exposure without any prior notice to the residents. This led to a surge in noise complaints and complainant from the residents. 2015 registered the maximum number of homes complaining, which rose to 1338, 28 times the average number of homes complaining between 2010-2013. The number of noise complaints kept increasing after the NextGen adoption until the path reversal and in the year 2017, it witnessed more than 100,000 noise complaints.

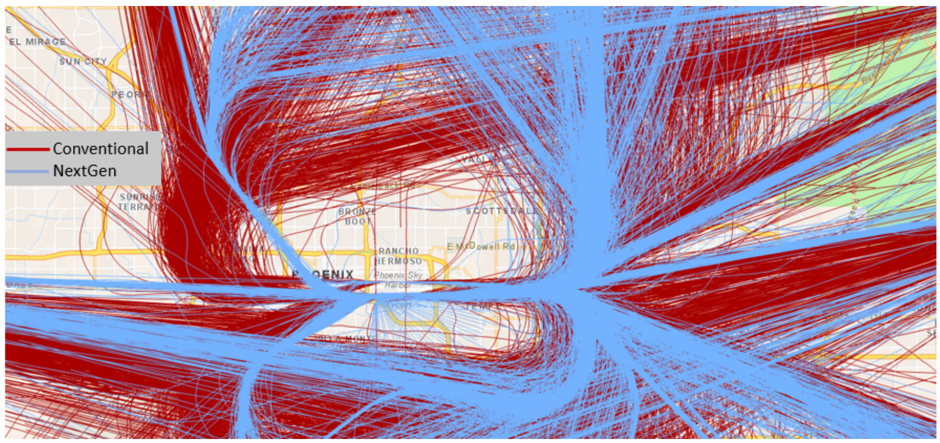
On June 1^{st} 2015, the City of Phoenix filed a lawsuit against the FAA over flight path changes, alleging that the agency has negatively impacted the Phoenix community without proper due process, notification, and consideration Report (2016). Shortly following the City's petition, impacted historic neighborhoods (northwest region of the airport), and the City of Phoenix filed suit against the FAA. After a court-ordered mediation without any resolution in 2016, on August 29, 2017, the U.S. Court of Appeals ruled in favor of the City of Phoenix and historic neighborhoods' lawsuit against the FAA over flight path changes Report (2017). Partial policy reversal occurred by March-2018. I refer to it as a partial policy reversal, as only the westward departures were changed. The western departure corridor under the new phase was similar to the conventional phase but narrow. The panel B of the figure 1 shows departure flight paths in a week from three phases: conventional, NextGen, and policy reversal. Under the conventional, NextGen, and policy reversal, flight paths are shown in red, blue, and green, respectively.

3 Data

The section provides an overview of the databases used for the analysis, running regression, and model estimation. The data are categorized into three groups: flight path data, housing data, and demographic data.

The flight path data contain information about all flight operations during the 2nd week

A. Conventional and NextGen



B. Conventional, Nextgen and Reversal

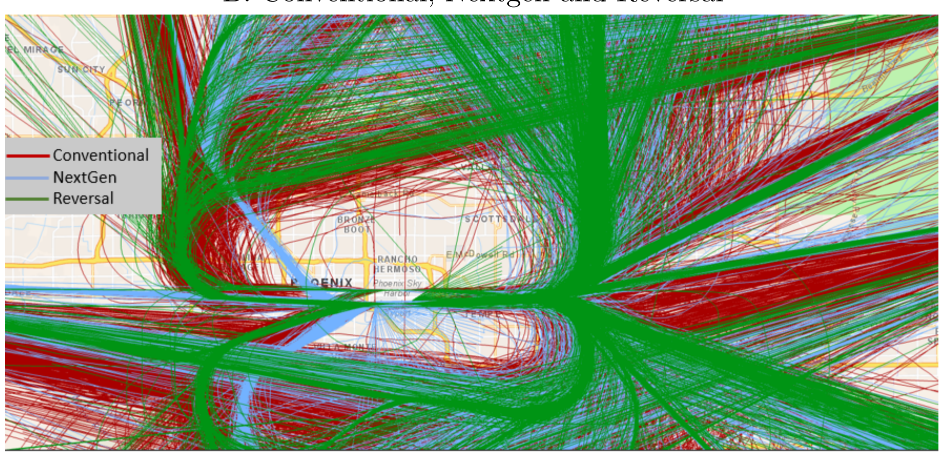


Figure 1: Flight Path (Departures) under different phases

Source: Phoenix Sky Harbor Airport.

The two set of figures shows the flight paths for a week under the three different phases: Conventional (red), NextGen (blue) and Reversal (green). Panel A shows the narrower and shorter flight paths under NextGen compared to the conventional. Panel B also displays the flight path upon reversal. The reversal flight paths are similar to those under conventional, but more concentrated.

of every month from 2010 to 2019. They include 3D GIS information on the flight paths, as well as details on the time of operation, airplane type, and origin/destination of the flight. I feed the flight path information into Aviation Environmental Design Tool (AEDT) which is a software system used by FAA nad various aviation thinktanks to estimate fuel consumption, emissions, noise, and air quality consequences.

The Assessor's Office of Maricopa County provides the housing data, and it consists of three datasets: property transaction data, property characteristics data, and property GIS shapefile. These datasets are matched using a unique parcel number. The property transaction data contain information on sale price, sale month-year, and buyer-seller information. Property characteristics data include details such as livable area, lot size, number of bathroom fixtures, pool area, garage and patio information, construction year, and parcel number. The property GIS shapefile provides the polygons for each property or parcel. I focus the analysis on the properties sold between September 2009 (5 years before NextGen adoption) and March 2020 (2 years after the policy reversal).

The DataAxle database contain information on family demographics like income, wealth, number of family members, and individual demographics of the family members. Each family is linked to the properties in Maricopa County where they resided. The ACS 5-year estimates are used to capture neighborhood demographic characteristics, including median household income, percentage of the white population, percentage of the black population, and percentage of the poor population.

The databases were merged through three steps. First, the family demographic data from DataAxle and housing data are matched using address, resulting in a successful match rate of about 90% for single-family residents. Second, neighborhood characteristics from the ACS data are linked to properties using ArcGIS Pro by matching the property centroids with corresponding block groups. Finally, noise exposure for different phases is assigned to properties using AEDT software. The flight path polyline is converted into GIS points using Python on ArcGIS Pro, and the data, along with flight operations information, is then converted into .xml format for input into AEDT. The AEDT software outputs noise exposure at a grid size of 0.25 miles X 0.25 miles, and I assign the noise exposure of each property based on the closest grid point. I use the flight paths of the operations between 2010 and 2019. As a result, the final dataset contains comprehensive information on property transactions, characteristics, neighborhood attributes, noise exposure during different phases, and household demographic characteristics.

The primary noise exposure measure used for analysis is DNL (day-night average sound level), as suggested by FAA and commonly used in the literature. AEDT is computationally intensive, so only 10% of randomly selected flight paths are used for analysis in groups (day, evening, and night).

3.1 Summary Statistics: Noise Exposure

Figure 2 displays the noise exposure map during the conventional phase. The map covers the region within a 20-mile radius from PHX airport, with the airport located at the center of the circle. Three concentric grey circles with radii of 5, 10, and 15 miles are visible on the map. For this analysis, a noise level of 40 dB has been established as the cutoff for the quiet zone, which is equivalent to the sound level of a quiet library. This is represented by the light blue color on the map. As a part of robustness checks, I run regressions with different cutoff noise levels, specifically 35 dB and 45 dB. For a comprehensive view of noise exposure under various phases, please refer to figure 11 in Appendix A.

Figure 3 illustrates changes in noise exposure. The map is divided into two sections, with the left side displaying the noise exposure change following the adoption of NextGen, and the right side showing the change following the policy reversal. The red and green regions represent an increase and decrease in noise pollution, respectively. The intensity of the color reflects the magnitude of the change, with darker shades representing more significant changes. Notably, some areas experienced noise pollution changes as high as 7 dB.

It is important to observe that the green and red areas in the two maps are symmetric.

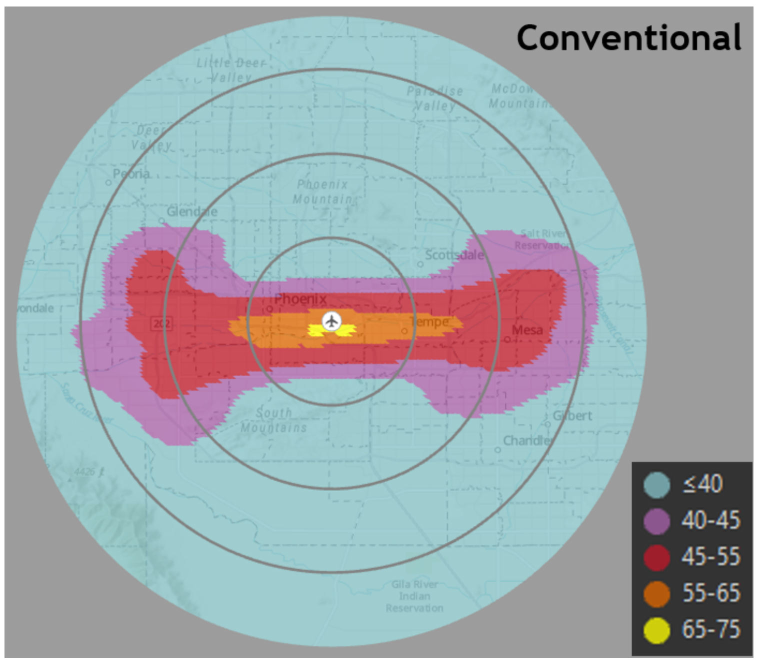
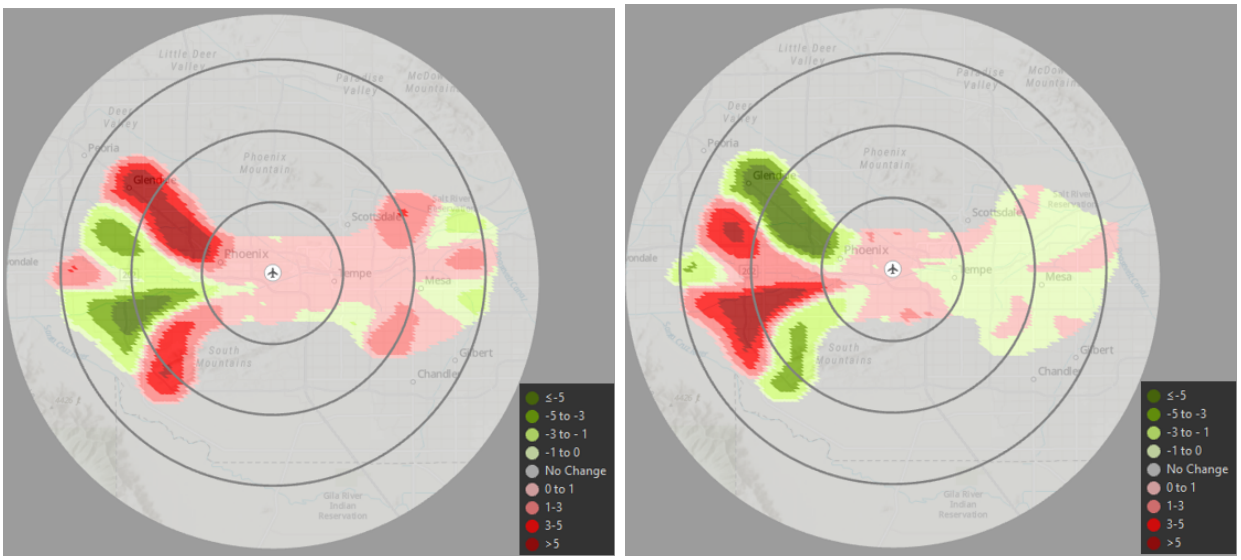


Figure 2: Noise Pollution under conventional phases

Source: generated by using AEDT on the flight path data provided by Phynoex SkyHarbor Airport
Note: Using the AEDT software and the flight paths under conventional phase, I generated the DNL, a noise pollution measure. This map shows the noise pollution (DNL) expressed in dB in the area within 20 miles from the airport. Phoenix Sky Harbor is in the middle of the map, and three gree circle represents the radii of 5, 10, and 15 miles.



A. Conventional to NextGen B. NextGen to Reversal

Figure 3: Noise Pollution Change

Source: generated by using AEDT on the flight path data provided by Phynoex SkyHarbor Airport
Note: These set of figures shows the distribution of the change in the noise pollution at two policy events: NextGen adoption, flight path reversal. The red and green regions represents the area with increase and decrease of the noise pollution, respectively. The darker shade represent a bigger change with some regions facing a change as big as 7 dB. The grey color represents the region with no noise pollution change.

Neighborhoods that saw an increase in noise pollution during the NextGen adoption phase subsequently experienced a decrease during the policy reversal. A similar pattern exists for areas where noise pollution decreased upon NextGen adoption. For a more detailed visual representation of the noise pollution changes from the conventional phase to the reversal phase, please refer to figure 12 in Appendix A.

Table 11 in Appendix A provides a breakdown of property counts based on the changes in noise exposure resulting from two flight path change events. In Panel A, it is evident that nearly 40% of the properties experienced no change in noise exposure as a result of either of the flight path change events. Specifically, NextGen adoption led to an increase in noise exposure for 41% of the properties and a decrease for 18%. Conversely, the flight path reversal resulted in increased noise exposure for 28% of properties and a decrease for 31%.

3.2 Summary Statistics: Property & Neighborhood Characteristics

In table 1, I conducted comparisons of property and neighborhood characteristics for properties facing an increase or decrease in noise exposure across the two events. In Panel A of Table 1, the analysis focuses on property characteristics, including the sale price index (sale price adjusted by the Case-Shiller index), lot size, living area, and vintage. Panel B, on the other hand, examines neighborhood characteristics such as the percentage of Black residents, percentage of White residents, median income, and median age in 2014.

The results presented in Table 1 indicate that properties facing an increase or decrease in noise exposure during either event exhibit statistically significant differences. Specifically, when comparing properties sold during the conventional phase, those facing an increase during NextGen adoption tend to have larger lot areas, smaller living areas, and older vintage compared to properties facing a decrease. However, there is no statistically significant difference in the sale price index. Moreover, when comparing properties sold during the NextGen phase based on the increase or decrease in noise exposure during the transition from NextGen to the policy reversal phase, similar patterns emerge.

In Panel B of Table 1 shows that the properties facing an increase tend to have a higher percentage of White residents, a lower percentage of Black residents, a lower median income, and a higher median age. Importantly, these differences are statistically significant.

4 Reduced-Form Evidence

This section presents reduced-form evidence of the impact of noise pollution on property values. I adapt the model from Rosen (1974) to estimate the marginal willingness to pay (MWTP) to avoid noise pollution. The empirical strategy employed involves utilizing spatial and temporal variation in noise pollution that arises from quasi-random variation in flight paths over time.

Table 1: Balance of groups

	Conventional to NextGen				NextGen to Reversal			
	Δ Change				Δ Change			
	Decrease	Increase	Δ	t-stat	Decrease	Increase	Δ	t-stat
Observations	9,233	22,847			13,576	11,174		
A. Property characteristics								
Sale price index	136,962	142,497	-5,535	-1.3	147,770	151,080	-3,310	-1.3
Lot area (sq. feet)	7,939	8,662	-723	-7.4	8,748	8,381	367	3.8
Living area (sq. feet)	1,877	1,686	191	23.7	1,715	1,830	-115	13.8
Vintage	22.7	41.3	-18.6	-66.8	45.0	34.2	10.8	33.8
B. Neighborhood characteristics								
White population (%)	0.68	0.72	-0.04	-18.4	0.75	0.69	0.05	24.6
Black population (%)	0.15	0.09	0.07	45.8	0.08	0.13	-0.05	-34.2
Median HH income ($)	55,240	48,529	6,711	24.3	49,919	54,107	-4,188	-13.8
Median age	30.4	33.1	-2.8	-31.9	33.6	32.0	1.5	16.6

Source: noise data generated flight path data provided by Phoenix SkyHarbor Airport, property characteristics data from the Maricopa county accessor office, and demographic data from the census survey
Note: This table compares various property and neighborhood characteristics for properties facing an increase or decrease in noise exposure across the two events (Nextgen adoption aur policy reversal).

To estimate the effect of noise pollution on property values, I assign the noise pollution levels to each property for three distinct phases: conventional, NextGen, and reversal. The hedonic Ordinary Least Squares (OLS) regression is then run, incorporating noise pollution, property, and neighborhood characteristics, and fixed effects at the block group level and the time of sale. Despite accounting for observable property and neighborhood characteristics, potential concerns of confounding remain. For example omitted variable bias might arise from unobserved property and neighborhood characteristics that are correlated with both noise and property values. One example could be how clean the neighborhood is. To mitigate this concern, I employ property fixed effects, i.e., I compare the price of the same property before and after the noise pollution change.

The hedonic price equation is represented by:

$$ln(price_{jkt}) = \alpha + \beta_N Noise_{jk\tau} + \gamma X_{jkt} + \theta N_{kt} + FE + \epsilon_{jkt} \tag{1}$$

In the equation above, the subscript jkt represents property j in neighborhood k (block group) sold at time t. β_N is the coefficient of interest. The variable τ denotes the phase (conventional, NextGen, or reversal) during which the property is sold. $Noise_{jk\tau}$ represents the noise exposure at the property sold during phase τ. X_{jkt} and N_{kt} are the observable property characteristics and observable neighborhood characteristics (at the block group level), respectively. The term FE represents various spatial and time-fixed effects and their interactions.

One of the most widely used indicators for describing the impact of noise on real estate prices is the Noise Sensitivity Depreciation Index (NSDI) (Szczepańska et al., 2015). Hence, the results are expressed in terms of NSDI, which measures the percentage depreciation in property value upon a 1 dB increase in noise exposure:

$$NSDI = \frac{\text{total \% depreciation in house price}}{\text{increase in noise exposure}} = -\beta_N \times 100 \tag{2}$$

Table 2 presents the results of regressing the log of property price on noise exposure. Four sets of regressions are run, represented by equation 1. The first three specifications are hedonic pooled cross-section regressions, while the last one is the property-level FE model. The hedonic pooled cross-section regressions are identified by the spatial and temporal variation in noise pollution, while the property-level FE regressions limit the identifying variuation to the policy-induced exogenous variation in noise pollution. The differences among the first three specifications (hedonic pooled cross-section) lie in the properties and transactions participating in the regression. Specification (1) includes all transactions, irrespective of the noise phase or transaction count. Specification (2) has only transactions of properties sold just once, while Specification (3) includes transactions of properties sold at least once in both conventional and NextGen phases. Specification (4) represents the property-level FE version of Specification (3) and mitigates concerns about omitted variable bias.

In column (1) of table 2, I find a significant coefficient of -0.0125, corresponding to an NSDI of 1.25%. This indicates that a 1 dB increase in noise exposure leads to a reduction of property value by 1.25%. As we refine the analysis by only including properties sold during both the Conventional and NextGen phases the estimated effect is 1.6% (specification 3). For the repeat sales data during the conventional and NextGen phases, the FE estimate shows an NSDI of 1.04%. (4) is my preferred specification as it addresses concerns related to time-invariant unobservable characteristics, reducing the potential for omitted variable bias. The presence of downward bias, as observed in the hedonic cross-sectional OLS estimates compared to the FE estimates, highlights the importance of using fixed effects in the analysis. To give a simple example, when noisy neighborhoods also have properties with low curb appeal, the hedonic pooled cross-section regression may mistakenly attribute the lack of curb appeal to the impact of noise pollution. By running a property type FE regression, I ensure that the curb appeal does not influence the estimation of the coefficient of interest.

Table 2: Regression Results

	OLS			FE
	(1)	(2)	(3)	(4)
Noise	-0.0125***	-0.0130**	-0.0158***	-0.0104***
	(0.004)	(0.004)	(0.003)	(0.000)
Any phase: all transactions	✓			
Any phase: sold just once		✓		
Conventional & NextGen			✓	✓
Observations	138,307	101,149	26,277	26,277
Adjusted R^2	0.787	0.794	0.759	0.806

Source: flight path data provided by Phoenix SkyHarbor Airport, property characteristics data from the Maricopa county accessor office, and demographic data from the census survey
Note: This table displays regression coefficient β_N from equation 1, which measures the percentage change in property value for 1 dB change in noise pollution.
Standard errors in parentheses and clustered at the interaction of block group and year of sale. All regressions includes zip code, city and the month of sale as FE. The dependent variable is the log of the sale price. Observable characteristics of the property include living area, lot area, garage dummy, patio dummy, pool area, number of bathroom fixtures, type of cooling, type of property, type of wall, type of roof, stories, vintage, etc. Observable characteristics of the neighborhood j (block group) include median household income, median age, percentage of the Black population, percentage of the White population, and percentage of the poor population.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The estimated NSDI values in this study are similar to those reported in the existing literature. Von Graevenitz (2018) research indicated an NSDI range of 0.1% to 1.4% for noise levels above 55 dB. Bateman et al. (2001), in their review of 18 studies conducted prior to 2001, found the mean NSDI from airport noise to be 0.5%. Similarly, Brandt and Maennig (2011) and Swoboda et al. (2015) reported NSDI values of 0.23% and 0.27%, respectively. Other studies by Ozdenerol et al. (2015), Szczepańska et al. (2015), Wilhelmsson (2000), and Anderson estimated NSDI in the range of 0.4% to 0.94%.

5 Residential Sorting Model

5.1 Conceptual Framework

I utilize a model based on the work by Bayer et al. (2007) to analyze the housing decisions of households. In this model, each household (i) determines the housing type (h) for each time period (t) based on the maximization of their utility. The analysis is conducted across three distinct time periods, corresponding to the three phases of noise exposure (Conventional, NextGen, and Reversal). The utility function takes into account both the observed and unobserved characteristics of the households.

I employ a two-step procedure used by (Berry et al., 2004) and Bayer et al. (2007) to estimate the coefficients of interest. In the first step, I maximize the likelihood function derived from the households' housing decisions using the methodology discussed by Berry (1994). This step provides the taste parameters λ^i_{ht} and the mean utilities

Given the heterogeneity among households, their preferences for different attributes of the housing types vary. The housing type selection is influenced by factors such as the location (block group) and specific attributes like square footage area and the direction of the noise exposure change. Each household, represented by 'i', derives a utility denoted as U^i_{ht} from the housing type 'h' during time period 't'.

$$U^i_{ht} = V(X_{ht}, N_{ht}, Z_i, p_{ht}, \xi_{ht}) + \epsilon^i_{ht} \tag{3}$$

In equation 3, the variable U represents the indirect utility, which is dependent on the housing type and neighborhood characteristics (X_{ht}), noise exposure (N_{ht}), price (p_{ht}), unobserved utility (ξ_{ht}), and an idiosyncratic error component (ϵ^i_{ht}). The observable household characteristics are denoted by Z_i, representing preference heterogeneity. Taste heterogeneity is captured through α^i when the utility is written as:

$$U^i_{ht} = \alpha^i_X X_{ht} + \alpha^i_N N_{ht} + \alpha^i_p p_{ht} + \xi_{ht} + \epsilon^i_{ht} \tag{4}$$

where α_X^i, α_N^i, and α_p^i represent the heterogeneity in preference for observed property-neighborhood characteristics, noise exposure, and price. he preference (α^i) of household i for choice characteristic j (where $j \in X, p, N$) can be expressed as follows:

$$\alpha_j^i = \alpha_{0j} + \sum_{l=1}^{L} \alpha_{lj} z_{lt}^i \tag{5}$$

In Equation (5), L represents the total number of observable household characteristics. α_{lj} represents the preference of household characteristic l for property characteristic j. For instance, a household with senior citizens might place a higher value on a quiet environment compared to other households. z_{lt}^i denotes the demographic characteristics of household i.

In each time period, a household chooses either a housing type or the outside option, depending on which one provides higher utility. At time t, household i opts to stay in housing type h^* if the following condition holds:

$$U_{h^*t}^i \geq U_{ht}^i, \qquad \forall h \neq h^* \tag{6}$$

To ensure consistency and asymptotic normality of the second-stage estimates, it is important for the number of households to grow at a relatively faster rate compared to the number of property types. In my analysis, I consider approximately 400,000 households and around 3,500 property types. Each property is categorized into different property types based on its location and square footage. Specifically, I divide all properties into terciles based on square footage, and properties within the same block groups and terciles of the area are assigned to the same property type.

5.2 Econometric Implementation

The econometric implementation of the model involves using equations (5) and (4) to derive equation (7), which decomposes the household utility into mean utility and deviation from the mean utility. The mean utility (δ_{ht}) captures the utility common to all households through the mean preference parameters (α_{0j}), while the deviation from the mean utility (λ^i_{ht}) represents household-specific parameters through interaction with individual characteristics (α_{lj}).

$$U^i_{ht} = \underbrace{\delta_{ht}}_{\text{mean utility}} + \underbrace{\lambda^i_{ht} + \epsilon^i_{ht}}_{\text{deviation from the mean utility}} \tag{7}$$

The mean utility and deviation from the mean utility can be expressed as follows:

Mean Utility:

$$\delta_{ht} = \alpha_{0X} X_{ht} + \alpha_{0p} p_{ht} + \alpha_{0N} N_{ht} + \xi_{ht} \tag{8}$$

Here, α_{0j} represents the mean preference parameters for the property type attributes (α_{0X}), noise pollution (α_{0N}), and price (α_{0p}). The mean utility captures the average utility across households.

Deviation from the Mean Utility:

$$\lambda^i_{ht} = \sum_{x_j=1}^{K} \left(\sum_{l=1}^{L} \alpha_{lx_j} z^i_{lt} \cdot x^j_{ht} \right) + \sum_{l=1}^{L} \alpha_{lp} z^i_{lt} \cdot N_{ht} + \sum_{l=1}^{L} \alpha_{lp} z^i_{lt} \cdot p_{ht} \tag{9}$$

In equation (9), α_{lj} represents the taste preference parameters for the property type attributes (total K attributes), noise pollution, and price. The deviation from the mean utility captures the household-specific parameters based on their individual characteristics (z^i_{lt}).

I employ a two-step procedure used by Berry et al. (2004) and Bayer et al. (2007) to estimate the coefficients of interest. In the first step, I maximize the likelihood function derived from the households' housing decisions using the methodology discussed by Berry (1994). This step provides the taste parameters λ^i_{ht} and the mean utilities (δ_{ht}). In the second step, I regress the mean utilities on the attributes of the property types to estimate the mean preference parameters. To address endogeneity concerns, I employ property type fixed effects and time-varying instrumental variables (IVs), which I will discuss in detail later.

The first step of estimation utilizes the households' location choice decisions to construct a likelihood function. This step employs the contraction mapping methodology to estimate the mean utilities such that the predicted market shares match the observed market shares. The unobserved preference term of households (ϵ^i_{ht}) is assumed to be independently and identically distributed. Assuming ϵ^i_{ht} is drawn from a Type 1 extreme value distribution, the probability of household i choosing property type h can be written as:

$$Pr^i_{ht} = \frac{\exp^{\delta_{ht}+\lambda^i_{ht}}}{\sum'_h \exp^{\delta_{h't}+\lambda^i_{h't}}} \tag{10}$$

The log-likelihood function can be written as:

$$LL = \sum_t \sum_i \sum_h I^i_{ht} \log\bigl(Pr^i_{ht}\bigr) \tag{11}$$

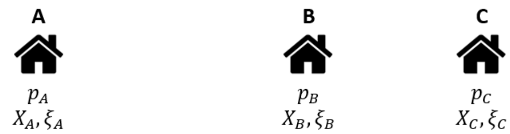
In equation (11), I^i_{ht} equals 1 if household i lives in property type h at time t, and 0 otherwise. Here, t refers to the phases (Conventional, NextGen, and Reversal).

The second step estimates the mean preference parameters by regressing the mean utilities on the attributes of the property types, as shown in Equation (8). The mean utility consists of two components: observable utility and unobservable utility (ξ_{ht}). The utility from unobserved attributes is likely to be correlated with the price and noise pollution of the property type. Generally, nicer neighborhoods or property types tend to have lower noise pollution and higher prices. To address endogeneity concerns, I employ a two-step process: first, I use temporal differences, and then I utilize time-varying instrumental variables (IVs). The term ξ_{ht} captures two aspects: (1) utility from time-invariant unobserved characteristics ($\bar{\xi}_{ht}$), and (2) utility from time-varying unobserved characteristics (ζ_{ht}). By employing property type fixed effects, I eliminate the time-invariant unobserved utility, as shown in the following equation:

$$\delta_{ht} = \alpha_h + \alpha_{0X} X_{ht} + \alpha_{0p} p_{ht} + \alpha_{0N} N_{ht} + \zeta_{ht} \quad (12)$$

However, there still remains utility from time-varying unobserved characteristics. To address this, I employ time-varying spatial IVs that are correlated with changes in price but not with changes in unobserved utility. The literature in industrial organization often uses the availability of close substitutes as instruments, as their availability affects the equilibrium price of a product. Bayer et al. (2007) developed IVs to capture the correlation between the price of a property type and unobserved utility. Figure 4a illustrates three property types: A, B, and C. As B and C are located closeby, p_C and ξ_B are likely to be correlated. However, as A and C are sizeable distance away, p_C and ξ_A are likely to be uncorrelated. Bayer et al. (2007) developed an instrument for price based on exogenous attributes of houses and neighborhoods located more than 3 miles away from a given house, while allowing attributes of houses and neighborhoods within 3 miles to directly affect utility. Using the same logic, I develop IVs that capture the correlation between changes in price and time-varying unobserved utility. Time-varying spatial IVs account for changes in the exogenous attributes of houses and neighborhoods that affect the change in the price of property type h, while not influencing the time-varying unobserved utility. Figure 4b demonstrates two properties, A and B. Properties within the rings surrounding these properties represent new similar properties developed at a sizable distance. An increase in the supply of properties around A leads to a reduction in the price of A compared to B. I assume that the changes in the exogenous attributes of houses and neighborhoods at a substantial distance are correlated with changes in price but not with changes in unobserved utility.

I follow a similar methodology of constructing IV in two steps as followed by Bayer et al. (2007). In the first step of constructing the instrumental variables (IVs), I estimate Equation (8) using a comprehensive set of controls and instruments for the price. Alongside the property type characteristics and neighborhood characteristics, noise pollution, and price, the set of controls also includes variables describing changes in land use within 1-mile rings



(a) Spatial IV

(b) Time Varying Spatial IV

Figure 4: Instrument Variables

Note: these set of figures gives intuition for the IV used to overcome the concerns of time-variant unobserved quality and change in price. Panel A illustrates three property types. As ameneties at a sizeable distance away doesn't affect the price, p_C is likely to be correalted with ξ_B, and not ξ_A. Panel B demonstrates two properties in the center. Properties within the rings surrounding these properties represent new similar properties developed at a sizable distance. An increase in the supply of properties around A leads to a reduction in the price of A compared to B. I use the variation in property supply and land use as IV.

around the property, extending up to 4 miles. To construct the IVs for the price, I deviate from the approach used by Bayer et al. (2007) and instead let the housing stocks and land use within 1-mile rings located between 4 and 8 miles around the property change with time. This modification allows me to capture the variation in property supply and land use changes, rather than their absolute levels.

The motivation for using these IVs stems from the idea that the availability of close substitutes impacts the equilibrium price of properties. By examining the change in housing stocks and land use, I aim to capture the exogenous variation in price driven by changes in the surrounding area, thereby reducing potential endogeneity concerns. Figure 5 illustrates the spatial variation in one of the IVs, namely the change in the area occupied by single-family residences from 2014 to 2018.

In the second step, my objective is to establish a more powerful instrument by using the estimates obtained in the first step. Specifically, I determine the market-clearing prices that effectively eliminate the influence of time-varying unobserved utility (ζ_{ht}). By setting ζ_{ht} to

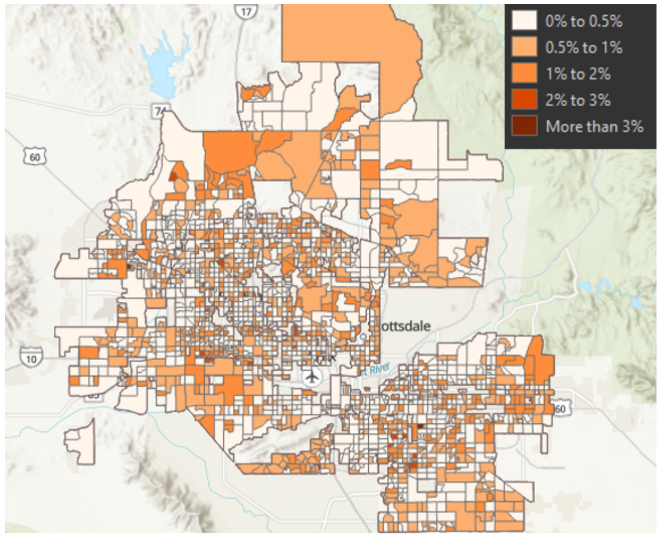


Figure 5: An example of time varying spatial IV

Note: I use the variation in property supply and land use in the one mile rings between 4 and 8 miles from the property as IV. This figure shows the the spatial variation in one of the IVs. It shows the change in area under single-family residences from 2014 to 2018.

zero, I ensure that the instrument is not affected by the variations in unobserved utility over time.

6 Results

Table 3 presents the mean Marginal Willingness to Pay (MWTP) to avoid 1 dB of noise pollution across four specifications that differ in how they address endogeniety concerns. Specification (1) defines a baseline for comparision. It lacks IVs and incorporates standard spatial controls such as indicators for city, zip, and block group. Specification (2) augments the standard controls with an additional spatial IV, similar to prior literature. Specifications (3) and (4) constitute novel contributions, addressing concerns pertaining to time-invariant and time-variant unobserved quality of property types. Specification (3) replaces the IV with property-type fixed effects to mitigate the impact of time-invariant unobserved locaction-specific factors. This adjustment leads to a mean MWTP similar to specification (2). Finally, specification (4) redefines the IV to address endogeneity concerns stemming from time-variant unobserved quality in addiotion to using property-type FE. This is achieved by using time-varying spatial IVs that are correlated with price changes but not with unobserved utility changes.

The mean MWTP to avoid noise pollution, without IVs, is estimated at over \$16,000. Introducing the standard IV (specification 2) reduces this estimate to around \$10,000. Applying the property-type fixed effects (specification 3) yields a similar mean MWTP. However, the most comprehensive approach (specification 4), addressing concerns of both time-variant and time-invariant unobserved quality, leads to a mean MWTP estimate of \$4,755. Notably, the standard IV in this context results in an overestimation of the effect by over 100%. One explanation of the finding is that the change in the noise pollution might bring other endogenous changes in the neighborhood, say the new quieter neighborhood is more cleaner. Ignoring the endogenous change in the ameneties would lead to an over estimation of the effect of the noise pollution as seen in specfications (1) to (3). Specfication (4) is my preferred specification and I use these parameters to estimate the welfare effect.

Table 3: Results: Mean MWTP

	(1)	(2)	(3)	(4)
MWTP per dB (\$)	-16,724	-10,080	-10,752	-4,755
Standard IVs		✓		
Prop. Type FE			✓	✓
Time variant IV				✓
Observations	6,246	6,246	6,246	6,246
Count of properties	293,676	293,676	293,676	293,676

Note: This table presents the mean MWTP to avoid 1 dB of noise pollution across four specifications. Specification (1) defines a baseline for comparision with any IV but withstandard spatial controls such as indicators for city, zip, and block group. Specification (2) augments the standard controls with an additional spatial IV, similar to prior literature. Specifications (3) and (4) constitute novel contributions, addressing concerns pertaining to time-invariant and time-variant unobserved quality of property types. Specification (4) relaxes the assumption on time-variant unobserved quality.

In my main specification (4), households' MWTP ranges from -\$2,948 to -\$6,683 depending on its charactertistics.

Table 4 summarizes how the MWTP varies by household income, age of the head, and race of the head. The mean MWTP increases with age, with households headed by individuals over 65 years exhibiting the highest MWTP. MWTP also increases monotonically across income quantiles. These monotonic trends are noteworthy because they are identified by flexible interactions between noise and group-specific dummies. Race H5 corresponds to the lowest MWTP among race categories, while Race DE reflects the highest MWTP.

Table 4: Mean MWTP by Demographic Attributes

Age Group		Income Group		Race (code)	
Group	Mean MWTP	Group	Mean MWTP	Group	Mean MWTP
Less than 30	-4,152	Q1	-3,792	00	-5,038
30-45	-4,572	Q2	-4,206	DE	-5,258
45-65	-4,809	Q3	-4,575	E5	-4,900
More than 65	-5,114	Q4	-5,089	H5	-3,744
		Q5	-5,878	S3	-4,904
				Others	-4,896

Note: This table shows the mean MWTP by household income, age of the head, and race of the head.

To delve deeper into the relationship between demographic attributes and MWTP, I look into the attributes of households with the highest and lowest MWTP values. Appendix B shows that the highest MWTP households are those in the top 20% of the income distribution with households head aged 65 or older. In contrast, the lowest MWTP households mostly stem from the bottom 40% of the income percentile. However, the H5 race category households constitute the household among the bottom 6.

7 Welfare

I utilize the residential sorting model to assess the welfare impact of a policy that modifies noise exposure. The welfare change represents the expected compensating variation for each agent derived from the alteration in their choice sets. I investigate this welfare change within both a partial equilibrium setting and a general equilibrium setting. The distinction lies in the fact that, within the general equilibrium framework, I allow prices to change in response to the change in noise exposure across the city. I estimate the new price equilibrium that clears the market.

To help interpret the results, I decompose welfare measures into three components: (1) a money-metric measure of the utility change at each household's current residence, (2) the equilibrium capitalization of the policy change into prices at that residence, and (3) the value to the household of being able to sort across the transformed landscape i.e. welfare because of the change in the choice sets. While the existing literature on the discrete choice model primarily concentrates on welfare effect from the change in the choice sets, the change in utility at the current residence warrants discussion within this framework. Attributes of products were modified subsequent to consumers' purchasing decisions, directly impacting their utility derived from the product. In contrast to consumables like cereals or cars, housing investments are made less frequently and entail significantly higher costs. They constitute two-thirds of the average homeowner's financial portfolio (Bayer et al., 2016).

For property owners, the dynamics differ. If a resident owns their home, the property price remains unaffected. Either the resident has already paid the price, or their monthly mortgage payments are contingent on the initial purchase price. Two perspectives emerge: first if the owner chooses to remain (continuing to occupy the purchased property), the monetary equivalent of the utility change within the PE setting. Second, suppose the owner opts to relocate (selling the property). In that case, the disparity between the price before and after the policy change can be interpreted as either a gain or loss of funds. Both partial and general equilibrium settings are employed to analyze the money-metric measure of the utility change at each household's current residence. For a resident experiencing heightened noise pollution, their utility diminishes. In a GE framework, the price of such a property would decrease, enabling the estimation of the change in utility for renters. Unlike property owners, renters are more likely to encounter reduced monthly rent costs. Consequently, a rental resident benefits from a price reduction. The change in utility of increased noise pollution is anticipated to be more detrimental for property owners than for renters.

7.1 Welfare Estimation

To estimate the change in welfare I focus on the compensating variation (CV):

$$\max_{h\in H^1}\left\{\alpha_X^i X_h+\alpha_N^i N_h^1+\alpha_{0p}p_h+\xi_h+\epsilon_{ih}\right\}=\max_{h\in H^2}\left\{\alpha_X^i X_h+\alpha_N^i N_h^2+\alpha_{0p}(p_h+CV)+\xi_h+\epsilon_{ih}\right\} \quad (13)$$

In the above equation, H_1 and H_2 represent the choice sets before and after policy shock. Noise exposures at property type h are expressed as N_h^1 and N_h^2. McFadden (1981), Small and Rosen (1981) show that for the T1EV distribution of the error, the expected value of the compensating variation for agent i can be expressed as:

$$\Delta \mathrm{W}_i^{PE}=\frac{1}{-\alpha_{0p}}\left[\ln\left(\sum_h e^{V_h^{i,2}}\right)-\ln\left(\sum_h e^{V_h^{i,1}}\right)\right] \quad (14)$$

where $V_h^{i,1}=\alpha_X^i X_h+\alpha_N^i N_h^1+\alpha_{0p}p_{ht}+\xi_h$ and $V_h^{i,2}$ is defined similarly.

$V_j^i=f(X_j,N_j,p_j,\xi_j;\alpha^i)$ is a function of the attributes of the products. $V_j^{i,1}$ and $V_j^{i,2}$ are the values corresponding to the noise levels N^1 and N^2, respectively. Note that the partial equilibrium measure holds prices fixed. To measure welfare in the general equilibrium setting, I use the following equation:

$$\Delta \mathrm{W}_i^{GE}=\frac{1}{-\alpha_{0p}}\left[\ln\left(\sum_h e^{\widetilde{V}_h^{i,2}}\right)-\ln\left(\sum_h e^{\widetilde{V}_h^{i,1}}\right)\right] \quad (15)$$

where

$$\widetilde{V}_h^{i,2}=\alpha_X^i X_j+\alpha_N^i N_h^2+\alpha_{0p}.p_h^2(X,N^2,\xi;\alpha)+\xi_h \quad (16)$$

Here, the new equilibrium price, p_h^2 is a function of all the attributes, unobserved utilities and preferences that clear the market after the change in the noise exposure.

I iterate over the following steps to solve for the new price equilibrium:

1. Decide the tolerance: mean of the difference between the aggregate demand and aggregate supply for each housing type. I set it to 10^-8.

2. For any price, calculate the aggregate demand for each housing type and determine if it corresponds to excess demand or supply.

3. In the case of excess demand, marginally reduce the price. In the case of excess supply, increase the price of the housing type incrementally. This step ensures incrementally increasing prices for housing types with excess demand and decreasing prices for those with excess supply.

4. Check the market clearning conditions: error defined as the mean of the aggregate demand and aggregate supply for each housing type is less than the tolerance. Iterate till the error is more than the tolerance.

7.2 Decomposing Welfare Changes

The estimation of the welfare effect because of the change in the current option is straightforward. For each resident, the change in utility under PE setting for an agent i residing at property h can be expressed as:

$$\Delta \mathrm{U}_i^{PE} = \frac{V_h^{i,2} - V_h^{i,1}}{-\alpha_{0,p}} \tag{17}$$

This equation ignores the change in the price of the property and therefore can be used to estimate the monetary equivalent of the change in the utility from the cutrrent option for the resident who is also an owner.

The welfare effect because of the change in the utility from the current residence under GE setting for an agent i residing at property h can be expressed as:

$$\Delta \mathrm{U}_i^{GE} = \frac{\widetilde{V}_h^{i,2} - \widetilde{V}_h^{i,1}}{-\alpha_{0,p}} \tag{18}$$

I perform a comprehensive welfare analysis encompassing various policy shocks, including NextGen adoption, NextGen adoption aligned with FAA guidelines, and NextGen reversal.

Within each welfare analysis, I outline the welfare changes, considering both partial equilibrium (PE) and general equilibrium (GE) frameworks. A comparative analysis of these metrics follows, accompanied by an explanation of the economic rationale underpinning the observed trends. Furthermore, I delve into the distribution of these welfare changes, classifying households based on the direction of noise pollution alterations. To provide a spatial representation of the noise pollution change, all categories of welfare changes, the marginal willingness to pay (MWTP) for noise pollution, and price adjustments within the general equilibrium context, I aggregate the data at the block group level. This approach enables me to visualize the geographical spread of these effects. Additionally, I highlight the diversity in welfare changes across different demographic groups and ownership categories, thereby demonstrating the heterogeneity of these effects. By systematically examining the welfare effects of each policy shock and understanding the distribution of these changes across different households and geographic locations, I aim to provide a comprehensive assessment of the potential economic implications of each policy measure.

7.3 Welfare analysis of NextGen adoption

Table 5 illustrates the distribution of noise pollution changes across the city due to Nextgen adoption. In the selected sample used in the model, approximately 14% of properties experienced an increase in noise pollution, while around 8% witnessed a decrease. The mean change for these groups was about 2 dB, with an overall mean increase of 0.1 dB across all properties.

Ironically, the policy's objective of mitigating residents' noise exposure by adjusting flight paths led to an unforeseen outcome. The redirection of narrow flight paths over densely populated regions inadvertently escalated noise pollution levels for numerous properties. Remarkably, of the properties subjected to altered noise exposure, almost 25% faced a considerable change surpassing 3 dB. A 3 dB alteration signifies a doubling in the frequency of noise-polluting events, marking it as a substantial change rather than a marginal one. In light of these noteworthy alterations in property attributes, it becomes reasonable to employ a model.

Table 5: NextGen: Noise Change Distribution

Statistics	Direction of Noise Change			Total
	Decrease	Increase	No Change	
Min	-7.4	0	0	-7.4
p25	-3.3	0.4	0	0.0
p50	-1.5	1.2	0	0
p75	-0.5	2.6	0	0
Max	0.0	8.8	0	8.8
Mean	-2	1.9	0	0.1
Count	23,509	42,571	227,596	293,676
Percentage	8%	14%	77%	100%

Note: This table shows the distribution of noise pollution changes across the city due to Nextgen adoption. In the selected sample used in the model, approximately 14% of properties experienced an increase in noise pollution, while around 8% witnessed a decrease. The mean change for these groups was about 2 dB, with an overall mean increase of 0.1 dB across all properties.

7.3.1 The Mean Effect

Table 6 outlines the average and total welfare changes in both the PE and GE scenarios, alongside the exhibited money-metric measure of the utility change at each household's current residence and price adjustments. The mean welfare gain per household under the PE setting, as computed using Equation 14, is estimated at \$3,796. On the other hand, under the GE framework and calculated through Equation 15, the mean welfare gain per household is approximated to be \$98. This substantial disparity in welfare gains occurs because the prices increased in neighborhoods where noise pollution diminished, and decreased in neighborhoods with increased pollution. It's important to note an approximate \$600 decline in average property values post-policy change. Remarkably, NextGen adoption not only prompted alterations in citywide noise exposure but also impacted the combinations of various attributes. Under the PE setting, the availability of newly quieter neighborhoods increased expected welfare by virtue of the enhanced range of options available, despite the rise in average noise pollution. However, in the GE scenario, price adjustments significantly decrease this expected welfare gain.

Table 6 summarizes the average and aggregate money-metric measure of the utility change within both the PE and GE frameworks. The modest 0.1 dB upturn in noise pollution corresponds to utility change of approximately -$517 under the PE setting. This can be construed as the monetary representation of the realized decrease in utility if residents remain homeowners and choose to stay. Conversely, if homeowners opt to relocate, the average price alteration registers a reduction of -$601. For renters subjected to the new prices within the GE setting, the change in utility assumes an average value of $84. This demonstrates that, in contrast to homeowners, renters experience an increase in their monetary equivalent of the change in utility from their current residence due to the adjusted prices following the policy changes.

Table 6: Welfare Change upon NextGen Adoption

Source of Welfare Change	Mean ($)	Total (Million $)
Welfare effect (PE)	3,796	1,115
Welfare effect (GE)	98	29
Change in utility (PE)	-517	-152
Change in utility (GE)	84	25
Price change	-601	-177

Note: This table outlines the average and total welfare changes in both the PE and GE scenarios, alongside the exhibited money-metric measure of the utility change at each household's current residence and price adjustments.

Figure 6 provides a visual representation of the mean welfare change, price change, and utility change from their current option across residents by the direction of the noise pollution change. The mean welfare change under both PE and GE settings (green color bars) is primarily influenced by residents' preferences rather than their specific locations. Consequently, these values exhibit minimal variance across different noise pollution change directions. However, the trajectory of price change and utility change (grey color bars) from the current option is contingent on the direction of noise pollution adjustments. Residents residing in areas where noise pollution decreased due to NextGen adoption observe a rise in property values. Under the PE setting, the mean money-metric measure of the utility change are $8,097, which is offsetted by $8,468 increase in the property price resulting in a loss of $370 under the GE framework. Similarly, the residents living in the properties facing an increase in noise pollution had a mean loss of $8,039 under the PE setting and a gain of $258 under GE. Although NextGen's impact is concentrated on 23% of properties altering their noise exposure, the price dynamics extend to encompass all properties. The policy's influence reshaped residents' choice sets and their housing decisions, subsequently triggering a $99 decline in property prices for those unaffected by noise pollution changes.

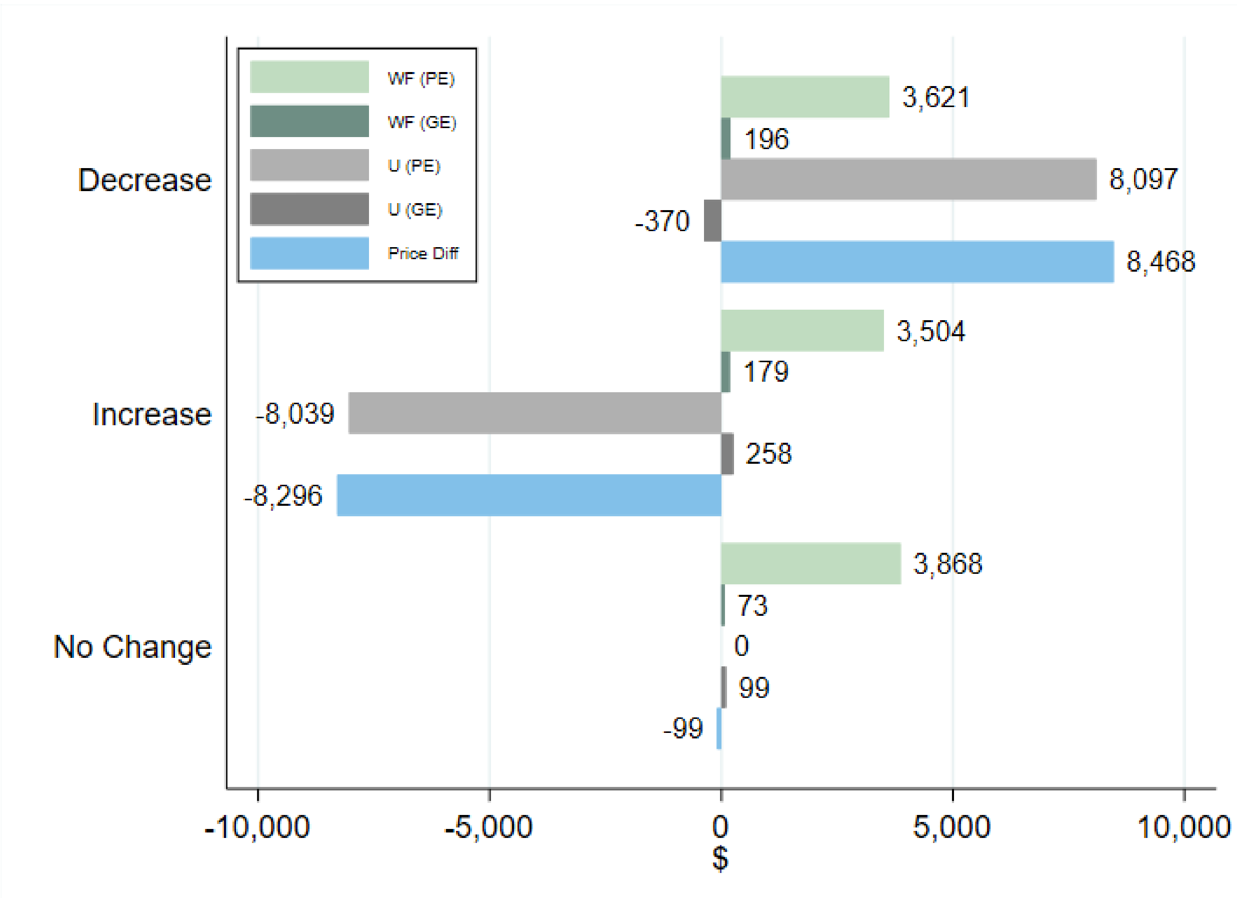


Figure 6: Mean Welfare Change upon NextGen Adoption

Note: This figure shows of the mean welfare change, price change, and utility change from their current option across residents by the direction of the noise pollution change. Green color bars represents the welfare effect because of the change in choice sets under PE and GE frameworks. The grey colored bars represents the money-metric of the change in utlity from residents' current option.

7.3.2 Heterogeneity in Effect

To assess the repercussions of the NextGen policy on residents, my analysis is centered around the money-metric measure of the utility change at each household's residence within the PE framework. This metric encapsulates the monetary equivalent of the post-purchase utility alteration for the product. In Table 7, I provide insight into the mean Marginal Willingness to Pay (MWTP) and average change in utility stemming from NextGen adoption across distinct demographic groups defined by various attributes integrated into the model. Notably, these attributes, including income, age, and race, contribute to households' preferences, thereby shaping their individual utility assessments. The table also showcases the mean price change within the GE framework for these diverse groups. A significant observation emerges within the context of income groups: the bottom 20 percentile, despite having the lowest MWTP to evade noise pollution, experiences the most pronounced impact due to NextGen adoption. Intriguingly, the eldest age group (aged over 65) exhibits the highest MWTP to avoid noise pollution yet simultaneously faces the most substantial loss. These insights underscore the intricate interplay between demographic attributes, residents' preferences, and the economic consequences of the NextGen policy, elucidating the differentiated impact experienced by distinct groups.

Figure 7 offers a graphical depiction of the distribution of noise pollution changes at the level of individual block groups. This visualization employs a color scheme to denote specific variations in noise pollution levels. The green and red segments indicate regions where noise pollution decreased and increased, respectively, in response to NextGen adoption. The blue area signifies locations where noise pollution remained unchanged following the policy implementation. It's important to note that the grey section in the figure corresponds to regions situated more than 25 miles away from the airport or tracts with insufficient property transactions, rendering them ineligible for inclusion in the analysis. This figure visually encapsulates the geographic distribution of noise pollution alterations across various regions, providing an at-a-glance understanding of the policy's spatial impact.

Table 7: NextGen: Mean Values by Demographic Attributes

Demographic Attribute	Group	MWTP	Change in Utility (PE)	Price change
Income Group	Q1	-3,792	-1,165	-1,459
	Q2	-4,206	-657	-749
	Q3	-4,575	-373	-415
	Q4	-5,089	-292	-312
	Q5	-5,878	-258	-280
	Total	-4,755	-517	-601
Age Group	Less than 30	-4,152	7	-65
	30-45	-4,572	-336	-448
	45-65	-4,809	-629	-727
	More than 65	-5,114	-736	-770
	Total	-4,755	-517	-601
Race (coded)	00	-5,038	-561	-608
	DE	-5,258	-554	-576
	E5	-4,900	-539	-600
	H5	-3,744	-406	-628
	S3	-4,904	-519	-577
	Others	-4,896	-532	-599
	Total	-4,755	-517	-601

Note: This table shows the mean MWTP, change in utility, and price change stemming from NextGen adoption across distinct demographic groups defined by various attributes integrated into the model. These attributes, including income, age, and race, determine households' preferences.

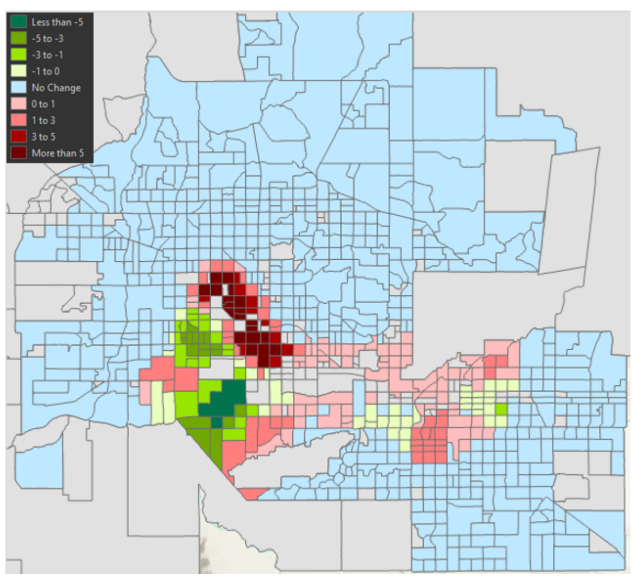
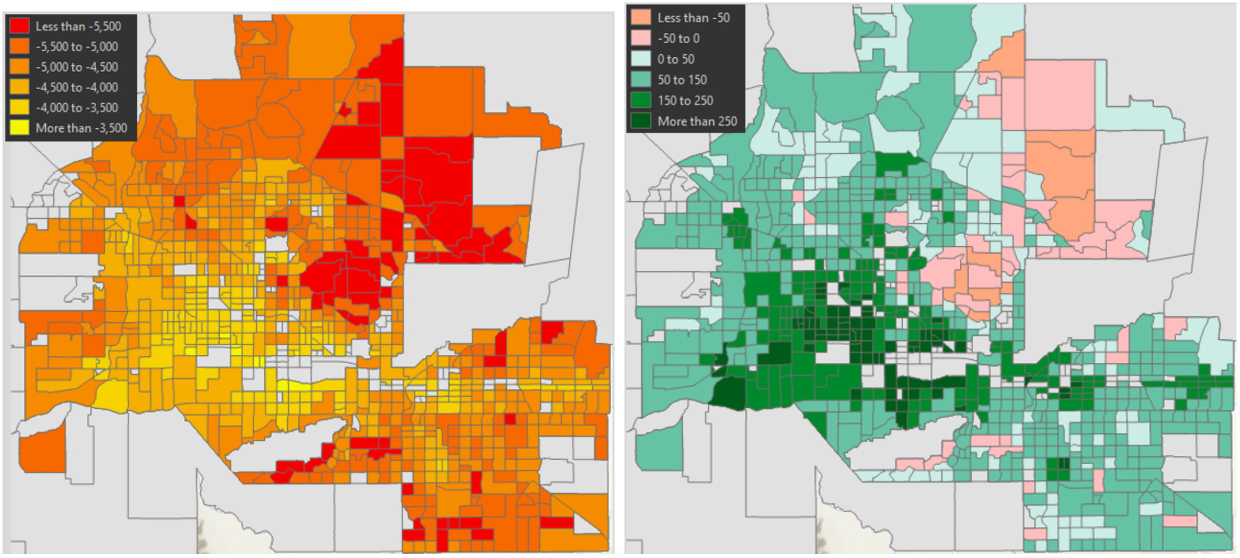


Figure 7: NextGen Adoption: Noise Pollution Change

Note: This figure shows the distribution of noise pollution changes at the block group level. The green and red segments indicate regions where noise pollution decreased and increased, respectively, in response to NextGen adoption. Areas with no noise pollution change is represented by the blue color.

Figure 8 establishes an insightful connection between the MWTP to avoid noise pollution and the resulting welfare change within the GE setting. The heatmap depicted in figure 8a showcases the mean MWTP at the block group level. Notably, areas in the northeast and southeast corners exhibit higher MWTP values, indicative of greater noise pollution aversion among residents in those regions. On the other hand, figure 8b illustrates the mean welfare change. The color spectrum employs green to represent gains and red to signify losses. The north-eastern and certain south-eastern tracts exhibit a welfare loss resulting from NextGen adoption that overlaps with the residents with a higher MWTP for quiet. This loss stems from a disparity in the number of properties experiencing a noise pollution increase (14%) compared to those experiencing decrease (8%), compounded by an overall rise in mean noise pollution. Consequently, the availability of quiet neighborhoods diminishes, leading to welfare losses for households prioritizing noise pollution avoidance, especially in the northeast region. Conversely, residents in the central area witness a welfare gain from the NextGen policy, potentially due to their lower MWTP for noise avoidance. These visualizations collectively shed light on the interplay between residents' preferences, the distribution of noise exposure changes, and the subsequent welfare outcomes arising from the NextGen policy. Welfare changes within the GE framework range from approximately -$90 to $400, with an average value of $84. These relatively modest figures reflect the inherent responsiveness of prices to noise exposure adjustments.



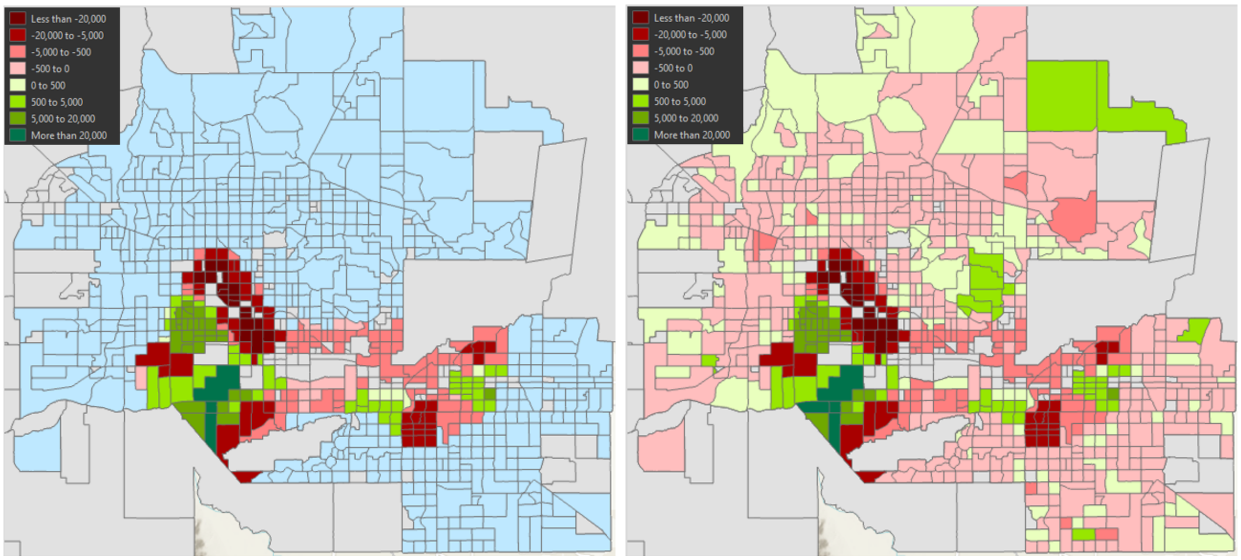
(a) Mean MWTP (b) Mean Welfare Change (GE)

Figure 8: Mean Welfare Change ($) at the block group level

Note: These set of figures shows the correlation between the MWTP to avoid noise pollution and the resulting welfare change within the GE setting. Panel A displays the showcases the mean MWTP at the block group level with the shade from yellow to red representing lower to higher MWTP to avoid noise pollution. Panel B shows the distribution of the mean welfare change under GE setting with green and red color representing gain and loss, respectively.

Figure 9 offers a spatial depiction of the average monetray equivalent of the change in utility from the current option and mean price change at the block group level. The visual representation in figure 9a showcases the average effect under the PE scenario following NextGen adoption. The color spectrum uses red and green to denote utility loss and gain, respectively, while blue indicates no change. Mechanically, this figure closely resembles figure 7, which illustrates noise pollution changes. The range of the change in utility spans from approximately -$35,000 to $30,000. Notably, regions where noise pollution remained constant also exhibit zero change in their utility from the current option.

Figure 9b elucidates the spatial distribution of price changes under the GE setting with red and green color representing a decrease and increase in the prices, repectively. The intuitive notion that properties experiencing an increase in noise pollution would observe a decrease in prices aligns with the figures discussed earlier (Figures 7 and 9a) within regions undergoing noise pollution changes. However, as the policy impacts residents' choice sets and subsequently alters market equilibrium, all properties are affected. Consequently, price changes within tracts where noise pollution remains constant exert a milder impact on prices (-\$500 to \$500).



(a) Mean Change in Utility from the Current Option (PE)

(b) Mean Price Difference

Figure 9: Change in utility from the current option and mean price change at the block groups level

Note: These set of figures shows the average monetray equivalent of the change in utility from the current option and mean price change at the block group level upon NextGen adoption. In panel A, the red and green colors represents utility loss and gain, respectively, while blue indicates no change. In panel B, price changes under the GE setting is represented with the red (decrease) and green (increase) colors.

7.4 The Policy Reversal

NextGen's implementation occurred without any prior notification to the residents. Subsequent to this alteration, PHX Airport experienced a staggering 30-fold surge in household complaints in 2015 compared to the period prior to the route change. The number of complaints soared from an average of 150 per year before NextGen adoption to over 100,000 in 2017. Responding to the flight route adjustments, the historic neighborhoods of Phoenix and the City of Phoenix administration initiated legal action against the FAA in June 2015. The court's verdict, delivered in favor of the plaintiffs in August 2017—almost three years after the initial flight route modifications—led to a partial policy reversal in March 2018.

This reversal entailed making westward departures more akin to conventional flight paths, albeit narrower.

In light of the shifts in noise pollution direction brought about by these two events, residents can be categorized into two groups: winners and losers. The "winners" group comprises residents whose properties experienced increased noise pollution during NextGen adoption but witnessed a decrease following the policy reversal. Conversely, the "losers" group encompasses residents whose properties benefited from the computer-generated flight paths during NextGen adoption but faced noise pollution increases upon the route reversal.

Table 8 delineates the average welfare change resulting from the policy reversal, comparing it to both the NextGen adoption and the conventional flight phase. The second column reflects the impact of NextGen adoption, which we discussed earlier. The third column compares the policy reversal's effects concerning NextGen, while the last column compares the same with respect to the conventional phase. While the NextGen adoption yielded a meager welfare gain (under GE setting) of only \$98 per household, the majority of this gain dissipated upon the policy reversal, resulting in an average welfare gain of \$8 from the conventional phase to the reversal phase. Interestingly, the change in utility from the current option and price change experienced more significant fluctuations. NextGen adoption led to an average loss of \$517, yet a substantial portion of this loss was mitigated by the policy reversal, resulting in an average loss of \$283 when compared to the conventional phase.

Table 8: Mean Welfare Change Across All Policies

Source of Welfare Change	Conventional to NextGen	NextGen to Reversal	Conventional to Reversal
Welfare effect (PE)	3,796	-3,827	-31
Welfare effect (GE)	98	-90	8
Change in utility (PE)	-517	234	-283
Change in utility (GE)	84	-75	9
Price change	-601	309	-292

Note: This table shows the average welfare change, change in utility from the current option, and price change resulting from the policies. The second column reflects the impact of NextGen adoption, which we discussed earlier. The third column compares the policy reversal's effects concerning NextGen, while the last column compares the same with respect to the conventional phase.

Table 9 summarizes how both policies influenced noise exposure across two distinct groups: winners and losers. The monetary equivalent of the utility change experienced by these groups due to the two noise exposure change events, while also presenting welfare effects under the GE framework. Notably, the number of winners is nearly double the number of losers, which can be attributed to NextGen's amplification of noise pollution over densely populated areas. Winners experienced a mean noise pollution increase of 2.5 dB during NextGen adoption, which was effectively reversed during the subsequent policy change, resulting in almost negligible change from the conventional phase to the reversal phase. This corresponds to a mean money-metric measure of utility loss of $10,088 due to NextGen adoption, offset by a nearly equal gain during the policy reversal.

In contrast, the losers encountered a mean noise pollution decrease of 2.6 dB during NextGen adoption, followed by a noise pollution increase of 3.4 dB upon the reversal. This increase in noise pollution during the reversal phase could be attributed to the narrower flight paths adopted due to technology advancements under NextGen. Surprisingly, their mean noise pollution increased by 0.7 dB from the conventional phase to the reversal phase, akin to taking one step forward and two steps back. Despite these dynamics, the welfare change under the GE setting displays minimal variation between winners and losers.

Table 9: Comparing Winners and Losers

		Losers	Winners	Total
		16,454	30,316	46,770
Noise change (dB)	Conventional to NextGen	-2.6	2.5	0.7
	NextGen to Reversal	3.4	-2.4	-0.4
	Conventional to Reversal	0.7	0.04	0.3
Money-metric measure of utility change (PE)	Conventional to NextGen	10,512	-10,088	-2,841
	NextGen to Reversal	-13,371	9,743	1,611
	Conventional to Reversal	-2,859	-345	-1,230
Welfare change (GE)	Conventional to NextGen	224	188	200
	NextGen to Reversal	-145	-133	-137
	Conventional to Reversal	79	55	63

Note: This table summarizes the impact of two policies of two groups: winners and losers. The impact is measures by the mean noise pollution change, money-metric measure of the utility change, and welfare change.

Table 10 presents a comparison of demographic attributes between the winners and losers groups. The analysis focuses on three key demographic characteristics: income, age, and race. While the difference in income group distribution between winners and losers is not stark, there are discernible trends in age and race compositions.

When considering income groups, winners exhibit a slightly higher percentage of households within the top 40 percentile of income compared to the losers (17% vs. 11%). However, the more pronounced disparities emerge when observing age and race attributes. Winners and losers diverge more noticeably in terms of age distribution. In the losers group, half of the households have the head of the family aged 45 or more, whereas in the winners group, this age bracket constitutes two-thirds of the households. Moreover, the percentage of households with heads aged 65 or older is higher in the winners group.

These findings underscore the differences in age and race composition between the two groups, highlighting that the impact of noise exposure policy changes can be influenced by these demographic factors.

Table 10: Winners and Losers: Demographic Attributes

Demographic Attribute	Group	Losers	Winners
Income Group	Q1	37%	36%
	Q2	32%	28%
	Q3	21%	20%
	Q4	9%	11%
	Q5	2%	5%
Age Group	Less than 30	16%	10%
	30-45	33%	27%
	45-65	39%	44%
	More than 65	13%	19%
Race (coded)	00	4%	6%
	DE	3%	5%
	E5	17%	23%
	H5	50%	32%
	S3	4%	6%
	Others	22%	28%

Note: This table shows the demographic composition of the winners and losers groups. The analysis focuses on three key demographic characteristics: income, age, and race.

References

J. K. Abbott and H. A. Klaiber. An embarrassment of riches: Confronting omitted variable bias and multi-scale capitalization in hedonic price models. *Review of Economics and Statistics*, 93(4):1331–1342, 2011a.

J. K. Abbott and H. A. Klaiber. The value of water as an urban club good: A matching approach to hoa-provided lakes. Technical report, 2011b.

L. Barregard, E. Bonde, and E. Öhrström. Risk of hypertension from exposure to road traffic noise in a population-based sample. *Occupational and environmental medicine*, 66 (6):410–415, 2009.

I. Bateman, B. Day, I. Lake, and A. Lovett. The effect of road traffic on residential property values: a literature review and hedonic pricing study. *Prepared for Scottish Executive and The Stationary Office, Edinburgh, Scotland*, 2001.

P. Bayer, F. Ferreira, and R. McMillan. A unified framework for measuring preferences for schools and neighborhoods. *Journal of political economy*, 115(4):588–638, 2007.

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

P. Bayer, R. McMillan, A. Murphy, and C. Timmins. A dynamic model of demand for houses and neighborhoods. *Econometrica*, 84(3):893–942, 2016.

S. Berry, O. B. Linton, and A. Pakes. Limit theorems for estimating the parameters of differentiated product demand systems. *The Review of Economic Studies*, 71(3):613–654, 2004.

S. T. Berry. Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262, 1994.

K. C. Bishop, N. V. Kuminoff, H. S. Banzhaf, K. J. Boyle, K. von Gravenitz, J. C. Pope, V. K. Smith, and C. D. Timmins. Best practices for using hedonic property value models to measure willingness to pay for environmental quality. *Review of Environmental Economics and Policy*, 14(2):260–281, 2020.

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

S. Brandt and W. Maennig. Road noise exposure and residential property prices: Evidence from hamburg. *Transportation Research Part D: Transport and Environment*, 16(1):23–30, 2011.

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

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

J. P. Cohen, C. C. Coughlin, J. Crews, and S. L. Ross. Immediate and longer-term housing market effects of a major us airport closure. Technical report, National Bureau of Economic Research, 2021.

L. W. Davis. The effect of health risk on housing values: Evidence from a cancer cluster. *American Economic Review*, 94(5):1693–1704, 2004.

S. Galiani, A. Murphy, and J. Pantano. Estimating neighborhood choice models: Lessons from a housing assistance experiment. *American Economic Review*, 105(11):3385–3415, 2015.

T. Hener. Noise pollution and violent crime. *Journal of Public Economics*, 215:104748, 2022.

N. V. Kuminoff, V. K. Smith, and C. Timmins. The new economics of equilibrium sorting and policy evaluation using housing markets. *Journal of economic literature*, 51(4):1007–62, 2013.

C. Lipscomb. Small cities matter, too: the impacts of an airport and local infrastructure on housing prices in a small urban city. *Review of Urban & Regional Development Studies*, 15(3):255–273, 2003.

D. McFadden. Econometric models of probabilistic choice. *Structural analysis of discrete data with econometric applications*, 198272, 1981.

E. Ozdenerol, Y. Huang, F. Javadnejad, and A. Antipova. The impact of traffic noise on housing values. *Journal of Real Estate Practice and Education*, 18(1):35–54, 2015.

J. C. Pope. 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, 2008.

A. N. Report. Noise report. Technical report, City of Phoenix Aviation Department, 2016.

A. N. Report. Noise report. Technical report, City of Phoenix Aviation Department, 2017.

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

M. Sklarz and N. Miller. The impact of noise on residential property value.

K. A. Small and H. S. Rosen. Applied welfare economics with discrete choice models. *Econometrica: Journal of the Econometric Society*, pages 105–130, 1981.

M. Sørensen, M. Hvidberg, Z. J. Andersen, R. B. Nordsborg, K. G. Lillelund, J. Jakobsen, A. Tjønneland, K. Overvad, and O. Raaschou-Nielsen. Road traffic noise and stroke: a prospective cohort study. *European heart journal*, 32(6):737–744, 2011.

A. Swoboda, T. Nega, and M. Timm. Hedonic analysis over time and space: the case of house prices and traffic noise. *Journal of Regional Science*, 55(4):644–670, 2015.

A. Szczepańska, A. Senetra, and M. Wasilewicz-Pszczółkowska. The effect of road traffic noise on the prices of residential property–a case study of the polish city of olsztyn. *Transportation Research Part D: Transport and Environment*, 36:167–177, 2015.

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

Vox. Why silence is a luxury — and why companies seek to capture it, 2018. URL https://www.vox.com/ad/17417806/history-silence-noise-headphones-anechoic-chamber.

M. Wilhelmsson. The impact of traffic noise on the values of single-family houses. *Journal of environmental planning and management*, 43(6):799–815, 2000.

A A. Background

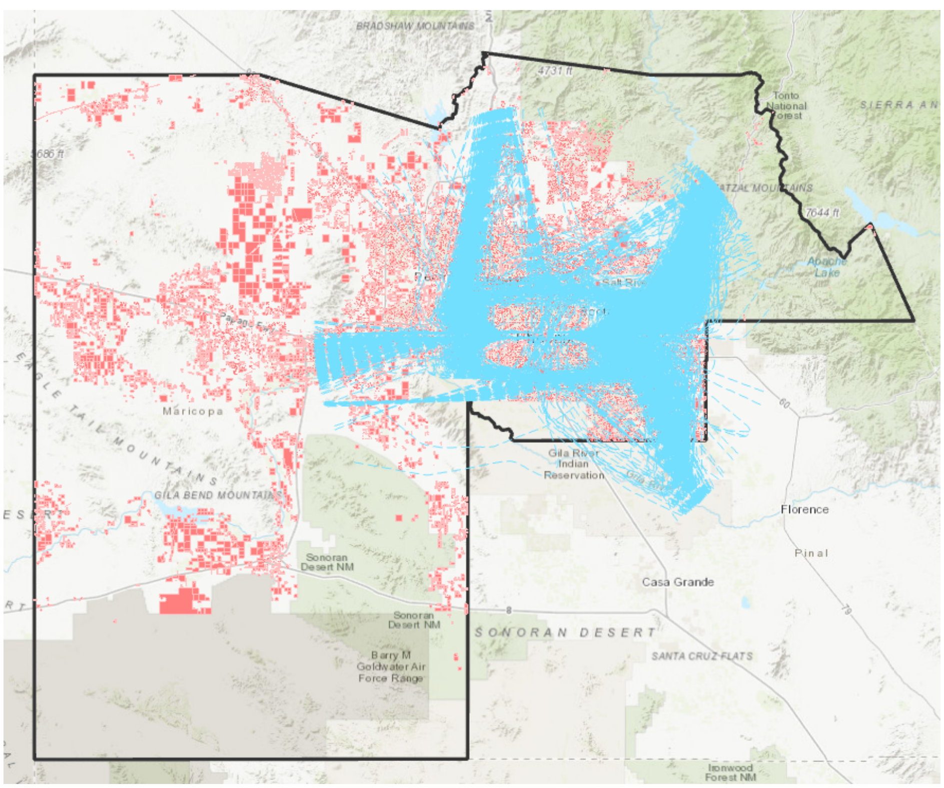


Figure 10: Parcels and a sample set of Flight Path

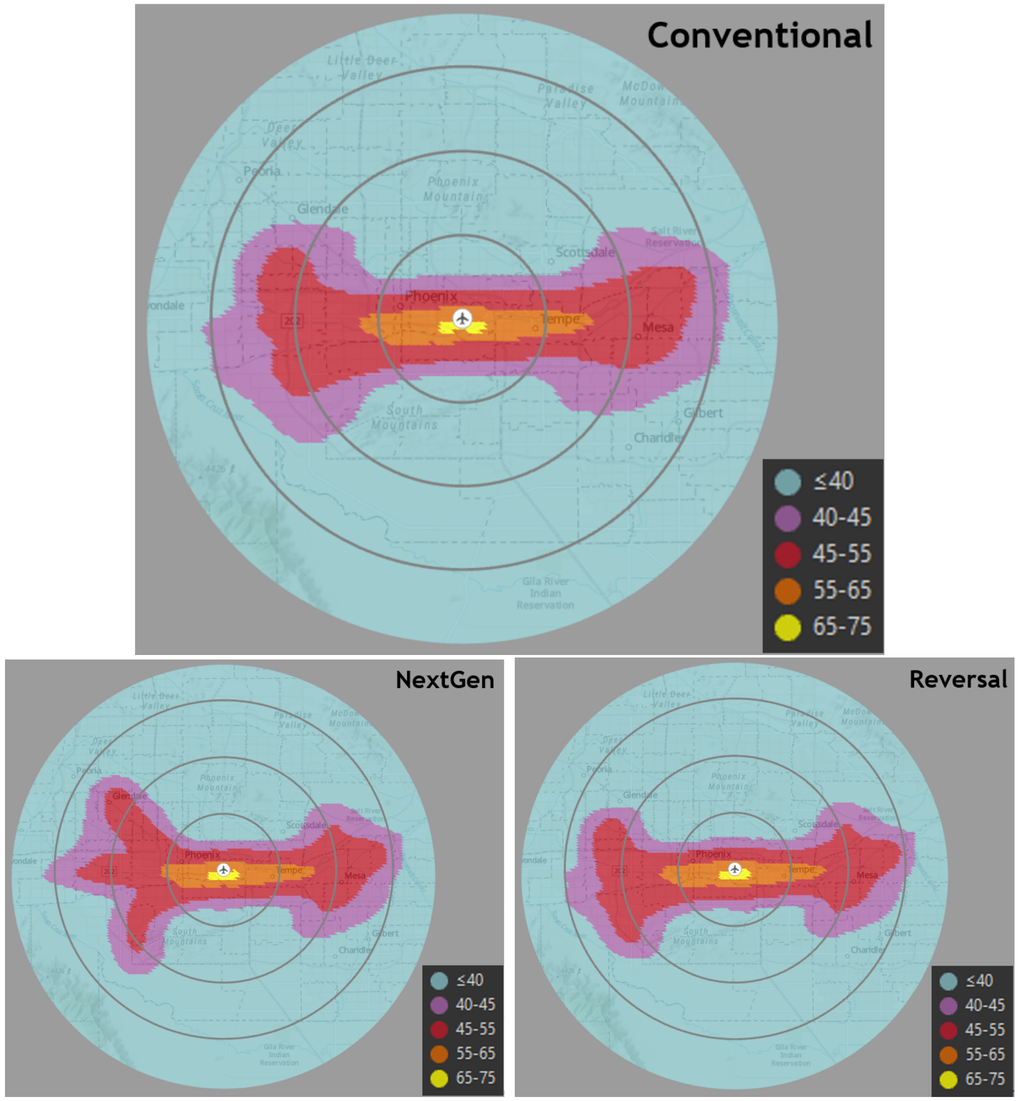


Figure 11: Noise Exposure under different phases

B Results

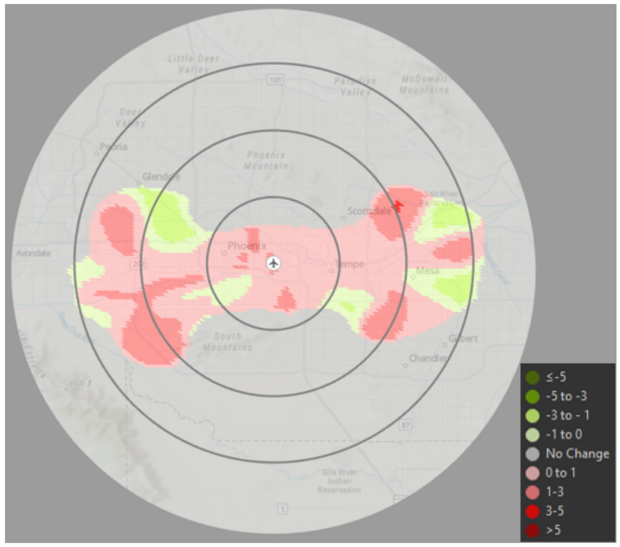


Figure 12: Noise Exposure Change from Conventional to Reversal

Table 11: Summary Statistics of Noise Exposure Change

A. Property counts for the two events

	Conventional to NextGen		NextGen to Reversal	
	Count	Percentage	Count	Percentage
Decrease	15,008	18%	25,990	31%
No Change	35,325	42%	35,325	42%
Increase	34,564	41%	23,582	28%
Total	84,897	100%	84,897	100%

B. Property counts across the two events

		NextGen to Reversal			
		Decrease	No Change	Increase	Total
Conventional to NextGen	Decrease	5,721	0	9,287	15,008
	No Change	0	35,325	0	35,325
	Increase	20,269	0	14,295	34,564
	Total	25,990	35,325	23,582	84,897

Table 12: Demographic Attributes of the Heightest and Lowest MWTP

Top 6				Bottom 6			
Income Group	Age Group	Race	MWTP	Income Group	Age Group	Race	MWTP
Q5	65+	DE	-6,683	Q2	45-65	H5	-3,539
Q5	65+	00	-6,535	Q2	Less than 30	H5	-3,488
Q5	65+	S3	-6,407	Q2	30-45	H5	-3,408
Q5	65+	E5	-6,407	Q1	45-65	H5	-3,079
Q5	65+	Others	-6,400	Q1	Less than 30	H5	-3,028
Q5	45-65	DE	-6,107	Q1	30-45	H5	-2,948