APPLIED ECONOMICS
https://doi.org/10.1080/00036846.2025.2547105

Routledge
Taylor & Francis Group

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The spatial effect of airport proximity on house prices: a quantile regression analysis for the New Zealand market

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ABSTRACT

This study contributes to understanding the link between the housing market and airport location proximity, whilst examining the entirety of the house price distribution. The research investigates this association across four key urban areas within New Zealand proximal to an international airport – Auckland, Wellington, Christchurch, and Queenstown. Applying hedonic and quantile regression, the analysis reveals that proximity to airports on house prices has a heterogeneous pricing effect. Results show that distance comprises a positive pricing effect within Auckland and Christchurch, whereas in Wellington and Queenstown the pricing effect is negative. The quantile regression findings further revealed differences between lower and higher priced properties value, given distance and proximity to airports within each city region. The Christchurch region reveals contrasting findings, showing there to be a higher positive pricing effect for higher-priced housing, which gradually decreases when moving down the quantiles. It is argued that this higher positive pricing for higher priced properties is due to particularities in the housing market close to Christchurch Airport.

KEYWORDS

Air-traffic activity; cities; amenities; hedonic price model (HPM); heterogeneity

JEL CLASSIFICATION

R15 - Econometric and Input-Output Models; Other Models, C01 - Econometrics

I. Introduction

The housing market is a critical component of any economy, playing a significant role in shaping economic conditions regarding wealth and consumption, investments and infrastructure construction, mortgage and lending, migration, environment, and so on (Bui, Wen, and Sharp 2022; M. J. Mccord et al. 2018; Robstad 2018; Sanchis-Guarner 2023; Zhao et al. 2024). Consequently, a large body of the literature has examined the housing market in terms of house price determinants (Affuso et al. 2019; Mehta, Gupta, and Maitra 2023; Paramati and Roca 2019), housing affordability (Squires and Webber 2019; Squires et al. 2022; Wardrip, Williams, and Hague 2011), as well as the influences of the property market on other sectors and the economy at large (Bangura and Lee 2022; Coskun et al. 2020; Winke 2020; Zheng and Zhang 2013).

Most housing studies follow (and extend) the hedonic price model (HPM), which argues that the price of a product or a house depends on its characteristics and attributes (Chin and Chau 2003; Meese and Wallace 1991). While the fundamental attributes such as house size and number of bedrooms have been intensively examined (Bourassa et al. 2011; Han, Han, and Zhu 2018; Janet Ge 2009; Katrakilidis and Trachanas 2012), recently, there has been increasing attention on new geographical and environmental characteristics such as proximity to amenities and services, neighbourhood, natural landmarks, and local infrastructure (Bangura and Lee 2022; Bui, Wen, and Sharp 2022; DUBÉ et al. 2014; Heyman and Sommervoll 2019; Lieske et al. 2021; Ngo et al. 2023; Zabel and Guignet 2012).

For small economies like New Zealand, the housing market is even more important, since the property industry is the largest in the country, accounting for 15% of the total GDP and 9% of total employment (PCNZ 2022). The housing market, therefore, can affect the stability of the finance sector (RBNZ 2022) and influence other macro-prudential policies

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(OECD 2022). However, studies on the New Zealand property market are still limited (Funke, Kirkby, and Mihaylovski 2018; Ngo et al. 2025; Rehm and Yang 2021; Tsui et al. 2019), and few have extended the HPM to account for new geographical/environmental characteristics. One study, Ngo et al. (2023), examined the non-linear impacts of airport proximity on New Zealand's house prices, but acknowledged that a more spatially based framework would help explain such impacts more proficiently.

This study aims to bridge this research gap by applying a quantile regression approach to examine the spatial and wealth differences across the housing market in New Zealand, which may influence the relationship between airport proximity and house prices. Accordingly, our research question is: 'Do the impacts of airport proximity on house prices differ across different quantile distributions of the New Zealand housing market?'

Our empirical results reveal that properties of different quantiles in New Zealand respond differently to proximity to airports. While airport proximity can generally have negative impacts on property values due to the airport's negative externalities, it can also be a value-enhancing attribute for medium to high-quantile properties in certain cities, such as Christchurch. While such a market dynamic is often overlooked by property valuers, who typically assume that accessibility to infrastructure has a uniform impact on home prices across price tiers, our findings provide valuable insights for real estate valuation, particularly in the context of compensating property owners due to relocation arising from airport and urban infrastructure development projects. These insights also contribute to a deeper understanding of the complex dynamics within the housing market and can inform more targeted and equitable policymaking and urban planning decisions related to airport development.

The rest of this study is constructed as follows. The next section briefly reviews the relevant literature on airport proximity and house prices, with an emphasis on the spatial effect within this context. The Data and methodology are presented next, followed by the Empirical results, and then some Discussions. The last section concludes the paper.

II. Literature review

Airport proximity and housing prices

The impact of airport proximity on neighbouring communities and property values has been a subject of ongoing debate, with the literature divided on whether it constitutes an amenity or a disamenity (Affuso et al. 2019). The prevailing view has held that proximity to airports negatively affects property values, primarily due to increased exposure to aircraft noise and air pollution (Salvi, 2008). Early evidence supporting this perspective was provided by Nelson (1979), who suggested that housing within a 2 to 3 mile radius of an airport suffer significant depreciation due to noise. Subsequent studies have employed the Hedonic Pricing Model, introduced by Rosen (1974), to further quantify the specific negative impacts of airport noise. For instance, Espey and Lopez (2000) confirmed that in Nevada, U.S.A., homes close to airports with noise levels of 65 dB or higher are valued at USD 2,400 less than similar homes in quieter areas. Similarly, Tsao and Lu (2022) found in Taoyuan, Taiwan, that house prices fall by approximately USD 2356.02/dB in 60–64 dB zones and USD 3622.78/dB in areas ≥65 dB.

Despite the widespread use of the hedonic pricing method, empirical estimates of noise-related property depreciation vary considerably across studies. A meta-analysis by Schipper, Nijkamp, and Rietveld (1998) found that such differences are largely driven by contextual factors, including sample wealth, model specification, and study timing. Their findings suggest that airport noise effects are location-specific and should be interpreted in light of local housing market conditions.

In addition to noise, air pollution and traffic congestion are other negative impacts of airport proximity. For instance, Won Kim, Phipps, and Anselin (2003) have shown that a 4% increase in SO_2, a by-product of aircraft fuel combustion, can decrease the marginal willingness to pay by approximately USD 2,333. Moreover, Ossokina et al. (2023) comparing housing prices before and after improvements in traffic congestion found that halving traffic density can increase property prices by 1.5%. This finding indirectly demonstrates the significant impact of traffic congestion around airport areas on property values.

However, beyond these challenges, the proximity to the airport may present benefits for property values, particularly in terms of enhanced accessibility and economic opportunities (Tsui et al., 2017). Tomkins et al. (1998) found that house prices near Manchester Airport in the UK decrease with distance from the terminal but at a decreasing rate. Supporting this, Cohen and Coughlin (2008) found that the relationship between property value and Atlanta International airport distance exhibits inelasticity. Moreover, Ngo et al. (2023) found a U-shaped relationship between airport distance and house prices in New Zealand. Collectively, these studies suggest that proximity to airports can be seen as an amenity, due to the significant economic benefits outweighing environmental drawbacks in some urban contexts (Ihlanfeldt and Taylor 2004).

The spatial and property value distribution effects of airport proximity

Although existing literature has clearly discussed the amenities and disamenities associated with airport proximity, spatial and wealth disparities in these impacts may exist. Brueckner et al. (1999) emphasized that the spatial layout and distribution of amenities significantly influence residential choices, especially for different income groups. This reveals that amenity patterns differ across cities and wealth spectrum. In the airport proximity studies, Lipscomb (2003) found that variations in noise levels near airports in small cities did not significantly affect property prices. He pointed out that the benefits of proximity to airports outweigh the adverse impacts often caused by the relatively few infrastructures and the economic dependence of airports in small cities. Furthermore, Salewski et al. (2014) study into the impact of airports on the built environment indicates that the distance from the airport to the city centre is crucial when assessing property values.

In addition, Nelson (1979) and Schipper, Nijkamp, and Rietveld (1998) found that the negative impact of noise on property values was greater in neighbourhoods with higher average property prices. This may be related to the wealth of the residents and their different expectations of the living environment, as individuals 'voting with their feet' (Tiebout, 1956). Whitfield (2003) supported this finding with empirical research, noting that residents of wealthier communities complain more frequently about aircraft noise compared to those in poorer areas. Lindgren (2021) further confirmed that high-income families are more sensitive to airport noise and tend to move to quieter areas. Equally, Phun et al. (2015), for a case of the Ninoy Aquino International Airport, revealed that less affluent residents have a higher tolerance for aircraft noise; and when they benefit economically from increased job opportunities and business improvements, their tolerance increases even further.

The existing studies, consistent with Salvi (2008), reveal that negative impacts primarily arise from adverse environmental effects related to aircraft noise and air pollution, while the positive effects of proximity to airports are usually associated with economic benefits. Despite this, the spatial and wealth differences in the impact of airport proximity on property prices remain unclear. However, overlooking these differences could lead to biased estimates of the impacts of airport proximity, especially when weighing economic benefits against potential disamenities. Therefore, this study further provides evidence by examining the heterogeneous impacts of airport proximity in four major urban areas of New Zealand and the variations in property price distributions.

Based on the extant literature in the area, New Zealand offers a unique opportunity to investigate airport-related housing market dynamics, particularly when considered in contrast with more heterogeneous and complex global markets such as the US, China, or the EU. A key strength of the New Zealand case lies in the functional differentiation of its urban markets. Auckland is the country's largest metropolitan area and serves as the primary international gateway, with the most extensive airport infrastructure and a broadly diversified economy. Wellington, as the political capital, is characterized by complex topography and spatial constraints, which make air connectivity especially critical for intercity mobility and access. Christchurch, the principal city of the South Island, hosts a major regional airport that not only serves domestic needs but also acts as a strategic logistics base for Antarctic travels and agricultural exports.

Queenstown, in contrast, is a smaller urban centre but globally prominent as a tourism hub, where airport access is fundamental to both the local economy and real estate dynamics. These varied roles across cities allow us to test the sensitivity of airport-related externalities under different urban forms, market functions, and economic orientations, all within a unified national system.

In addition to this functional diversity, New Zealand's urban housing markets are embedded within a homogeneous institutional, cultural, and regulatory framework. All four cities share a common language, governance system, legal environment (British common law system), planning regime, and socio-environmental values, including high public awareness of sustainability and environmental standards. This degree of national consistency stands in contrast to jurisdictions like the US, EU or China, where inter-state or inter-regional disparities in policy, culture, and administration can be substantial. The relative institutional uniformity across New Zealand's cities therefore minimizes unobservable sample heterogeneity and strengthens the internal validity of our cross-market comparisons.

From a methodological standpoint, this national cohesion confers several analytical advantages. The use of more standardized data systems ensures a high level of comparability across urban centres, reducing the need for extensive statistical controls for institutional variation. In turn, this enables a more focused examination of the spatial economic mechanisms underpinning airport proximity effects, free from the confounding influences of disparate governance structures or planning policies that are often present in larger or more fragmented jurisdictions.

III. Data and methodology

Methodology

This research applies a critical realist approach, which relates to underpinning economic and consumer preference and choice reality of people making housing decisions based on house prices and amenity value such as proximity to airports. In this regard, Zhang and Tao (2020) argue that one could estimate the relationship between price and characteristics of a house following the HPM approach that

$$PRICE_{it} = \beta_0 + \beta_j X_{jit} + \varepsilon \tag{1}$$

where $PRICE_{it}$ measures the price of houses in suburb i sold in year t; X_{jit} is a vector of housing characteristics (including house size, number of bedrooms, etc.) of houses located in suburb i sold in year t; β is a vector of parameters to be estimated, and ε is the measurement error. It is noted that the five regions correspond to four international airports in New Zealand which are Auckland Airport, Wellington Airport, Christchurch Airport, and Queenstown Airport. Auckland Airport analysis covers the 2 district council regions that are closest to the airport. These four airports have the largest aviation activities in the country (Ngo and Tsui 2020). The logarithm of the dependent variable is applied within the modelling frameworks due to the computational efficiency and interpretability of the independent variable coefficients in terms of their elasticity to the dependent variable. Model (1) can then be re-written as follows:

$$\begin{aligned} InPrice_{it} = {} & \beta_0 + \beta_j X_{jit} + SIZE_{it} + DIS\_AIR_i + AGE \\ & + BEDS + BATHS + REGION \\ & + YEAR + \varepsilon \end{aligned} \tag{2}$$

where *InPrice* is the logarithm of property price; *SIZE* is the size of the property in square metres; *AGE* is the year the property was built; DIS_AIR_i measures the geographical distance between the centroid of a suburb i and the closest airport; *BEDS* and *BATHS* are the vectors of dummy variables which represent the number of bedrooms and bathrooms a property has; *REGION* is a vector of dummy variables representing the five regions of Auckland-Manukau city, Auckland-Papakura city, Wellington, Christchurch, and Queenstown; and *YEAR* is also a vector of dummy variables representing different quarters and the year from 2018 to 2022 the property transacted.

Data

The data applied within this study is derived from CoreLogic who provide information on property analytics, valuations, and sales transactions.[1] CoreLogic is a global leader in property information in the US, Australia, and New Zealand; the property data of CoreLogic has been widely used by commercial banks, mortgage advisors, insurers, and even the government (CoreLogic 2025). This study applies 75,715 sales transactions between 2018Q1 and 2022Q1 across four international airport cities of Auckland, Christchurch, Wellington and Queenstown in New Zealand. The data encompasses sales prices and property characteristics such as house size, number of bedrooms, and number of bathrooms. The data, and housing typology reality in New Zealand; is a dominance of 3-bedroom single-story single family detached dwellings. This Single Family Dwelling (SFD) dominance, is alongside a much smaller number of apartments in Auckland, and as a result, we do not dissect their types in our analysis.

Comparative units of administrative geographies were applied based on the size of the population and geographical expanse of each city. Notably, the Auckland 'Supercity', warranted the inclusion of both Manukau City and Papakura City given their geographical proximity to the airport. Overall, the data comprised 312 suburbs within the city regions to which cross-sectional analysis was conducted in order to calculate the average distance in kilometres from each suburb (centroid) to the airport to obtain a robust 'price-distance' fixed effect from 2018 onwards.

Table 1 presents the variables and their descriptions applied within the study. Given the nature of real estate data, the logarithmic of the sales price is used as the log-linear model helps normalize the dataset and ease of interpretation of the estimation effects (Knoke, Burke, and Burke 1980; Wooldridge 2016).

Table 1. Variables and descriptive statistics.

Variable	Description	Unit
Dependent variable		
Price	Transaction sales price	NZD
InPrice	Logarithm of Sales price	NZD
Explanatory variables		
SIZE	Property size	m2
BEDROOM	Number of bedrooms	Room(s)
YEAR BUILT	Year the property was built	Year
DISTANCE	Distance from suburb to airport	km
REGION	Suburb the property is located	dummy
YEAR	Year property transacted	years

Table 2 provides the descriptive statistics for the city/regions used within the study. The average price of properties sold in Auckland exhibits the highest average price across the four regions ($1,369,538), followed by Queenstown ($1,188,234), Wellington ($927,114) and Christchurch ($807,405) respectively. Properties located in Queenstown display the largest average size of 167.7 m2, with houses located in Auckland having the lowest average size of 130.3 m2.

IV. Empirical results

The empirical analysis applies a number of regression models to measure proximity of the four regions to the international airports for Auckland, Wellington, Christchurch and Queenstown. As observed in Table 3, the four regional models display an adjusted R^2 ranging between 69.7% (Auckland) and 58.9% (Queenstown). Examination of the variance inflation factor (VIF) statistics across the four models, although not reported here for the space-saving purposes, revealed that none of the variables to be elevated (> 3), therefore not displaying any collinearity or exerting undue influence on the regression models. Examination of the coefficients exhibit general conformance with exceptions in terms of magnitude and direction, but some differences across the regions in terms of the magnitude of the pricing effects. For example, every unitary increase in property size (m^2) equates, *ceteris paribus*, to a 0.2% effect on house prices in Auckland, whereas in Queenstown this equates to a 0.4% pricing effect (Table 3).

In terms of the property age coefficients, the models exhibit a negative pricing effect, albeit at different magnitudes. The findings suggest that, on average, that a ten-year increase in the age of housing shows a negative pricing effect ranging between 1.0% (Christchurch) and 3.0% in Queenstown. To further examine this finding, we tested the coefficients on the squared term of building age, with the results showing this to be positive and statistically significant. This suggests that the negative effect of building age on house prices seems to diminish over the lifespan of the building. The number of

[1]See: http://www.propertyvalue.co.nz.

Table 2. Descriptive statistics.

	Mean	SD	Min	Max
Wellington				
Price	927,114	879,719	122,000	19,000,000
Size (m2)	140.23	106.58	14.00	4167.00
Bedrooms	3.00	1.03	1.00	7.00
Bathrooms	1.00	1.56	1.00	5.00
Year Built	1972	35	1865	2022
Distance	6.37	4.29	0.56	19.50
Christchurch				
Price	807,405	511,427	102,500	17,000,000
Size (m2)	146.47	76.86	18.00	3660.00
Bedrooms	3.01	0.87	1.00	6.00
Bathrooms	1.48	0.67	1.00	6.00
Year Built	1981	33	1870	2022
Distance	10.74	5.77	2.38	52.24
Auckland				
Price	1,369,538	1,107,598	115,000	18,795,000
Size (m2)	130.33	76.92	13.00	739.00
Bedrooms	2.77	1.10	1.00	6.00
Bathrooms	1.48	0.74	1.00	5.00
Year Built	1977	35	1880	2021
Distance	14.80	5.01	7.58	34.62
Queenstown				
Price	1,188,234	1,147,429	109,200	17,500,000
Size (m2)	167.69	112.48	23.00	506.00
Bedrooms	3.40	0.92	1.00	6.00
Bathrooms	1.81	0.87	1.00	6.00
Year Built	2005	17	1890	2022
Distance	31.01	75.67	0.48	134.84

Table 3. Regional average pricing effects with proximity to international airports.

	Christchurch	Auckland	Wellington	Queenstown
Constant	12.6513***	7.9383***	16.347***	25.264***
Size (m^2)	0.0024***	0.0020***	0.002***	0.004***
Age	0.0009**	−0.0012***	−0.0010***	−0.0031***
Dis Airport	0.0098***	0.0066***	−0.0222***	−0.004*
Beds 1	−0.0898**	−0.1348***	−0.1243***	−0.054**
Beds 2	−0.0155**	−0.0629***	−0.063***	−0.046*
Beds 4	0.0705***	0.0569***	0.015**	0.073***
Beds 5	0.0797***	0.0298***	0.028***	0.157***
Beds 6	0.0276	0.0196	0.008	0.257***
Baths 2	0.0509***	0.0076***	0.189*	0.081***
Baths 3	0.1090***	0.0071*	0.148**	0.015
Baths 4	0.1689***	0.0154**	0.194*	0.063**
Baths 5	0.1617***	0.0775***	0.163*	0.042*
Suburb-fixed effect	Yes	Yes	Yes	Yes
Time-fixed effect	Yes	Yes	Yes	Yes
R^2	.591	.699	.636	.610
Adj. R^2	.589	.697	.630	.604
F-statistic	258.214***	884.906***	192.951***	100.986***
N	21,926	32,291	15,358	6,140

"*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level, respectively. Parsimonious models are presented. Suburbs totalled 54 for Auckland; 56 for Wellington; 32 for Queenstown and 94 for Christchurch. Quarterly time periods: Q1,2018-Q1,2022.

bedrooms and bathrooms exhibit expected positive and negative effects. For example, one- and two-bedroom properties within the four regions reveal negative pricing effects, again at varying magnitudes, ranging between 13.5% in Auckland, to 5.4% in Queenstown relative to the hold-out three-bedroom properties.

With regards to proximity to airports, the findings exhibit mixed pricing effects across the four regions. Both Auckland and Christchurch display positive effects of 0.98% and 0.66% which are statistically significant at the 1% level. Conversely, Queenstown exhibits a nominal negative pricing effect of 0.1%, with Wellington showing a larger negative pricing effect with proximity of 2.1%.

The Quantile regression regional models reveal some stark and contrasting findings and provide nuanced insights as to the effects of proximity to

Table 4. Quantile regression regional models (Auckland).

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
Constant	5.860864***	6.972232***	7.678472***	7.894395***	8.24723***	8.419481***	8.725376***	9.271772***	9.236794***
SIZE (m^2)	0.001358***	0.001466***	0.001556***	0.001626***	0.001856***	0.001695***	0.001735***	0.001796***	0.001758***
Age	−0.001482***	−0.00147***	−0.001529***	−0.001521***	−0.001862***	−0.001599***	−0.001602***	−0.001738***	−0.001433***
Dis Airport	0.156421***	0.097196***	0.066129***	0.053853***	0.069667**	0.034***	0.017605***	0.003286	−0.029883**
Beds 1	−0.296804***	−0.291675***	−0.278706***	−0.268426***	−0.213879***	−0.228112***	−0.221294***	−0.202768***	−0.178338***
Beds 2	−0.068349***	−0.07034***	−0.061123***	−0.056131***	−0.040644***	−0.044483***	−0.03495***	−0.028086***	−0.006577
Beds 4	0.006866	0.004835	0.000489	0.002104	−0.005908	0.001395	−0.000784	−0.000822	−0.00246
Beds 5	0.016519	0.007908	0.021639***	0.024845***	0.037412***	0.019265***	0.022034***	0.022012***	0.032137***
Beds 6	0.058718***	0.083647***	0.082981	0.077588**	0.082773***	0.00217	0.055856**	0.026619	0.060027**
Baths 2	0.014009**	0.013282***	0.014794***	0.010196***	0.007661***	0.009544***	0.007516**	0.007842**	0.006028*
Baths 3	0.035686***	0.034379***	0.038197***	0.028486***	0.024928***	0.01896***	0.014678***	0.010208**	0.020634*
Baths 4	0.031866	0.052119***	0.041453***	0.034885***	0.045994***	0.055003***	0.026183**	0.023083	0.060505***
Baths 5	0.074523***	0.028952	0.048875*	0.029888	0.015913***	0.021904	0.076048***	0.064058***	0.093386***
Suburbs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.582541	0.536385	0.525626	0.521821	0.534156	0.511882	0.511733	0.506976	0.501349
Adj. R^2	0.578967	0.532416	0.521565	0.517728	0.527831	0.507703	0.507553	0.502755	0.49708
S.E. of regress.	0.223382	0.169508	0.15255	0.145559	0.154962	0.150019	0.171154	0.175906	0.350385
Quantile depen.	5.834421	5.939519	5.993436	6.054996	6.104529	6.155336	6.212853	6.278754	6.390405
Sparsity	0.456441	0.301873	0.251063	0.21806	0.218565	0.217229	0.235978	0.294134	0.452698
Prob(Quasi-LR)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

"*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level respectively. Parsimonious models are presented. Location and time dummy variables available upon request. Suburbs totalled 54 for Auckland; 56 for Wellington; 32 for Queenstown and 94 for Christchurch. Quarterly time periods: Q1,2018-Q1,2022. VIF and Tolerance statistics available upon request. Huber Sandwich Standard Errors & Covariance. Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall Sheather.

airports relative to the conditional mean OLS coefficient estimates. For Auckland (Table 4), there are manifest differences across the price distribution on the pricing effects of proximity to the airport. Overall, there appears to be a distance decay effect moving from the lowest to the highest quantiles. At the lowest quantile (tau = 0.1), the is a positive pricing effect of 15.6% which is statistically significant at the 1% level. The magnitude of the pricing effect diminishes to 9.7%, 6.6% and 5.4% between the 2nd and 4th quantiles (tau = 0.2–0.4) of the price distribution. Moving beyond the mean conditional estimate, there continues to be an erosion of the positive nature of the pricing effect with proximity. Between the sixth and eighth quantiles of the price distribution the size of the effect decreases from 3.4% to 0.3%, which are statistically significant at the 5% and 1% levels. The highest quantile exhibits a negative pricing effect of 3.0%, illustrating that the highest priced properties consider closer proximity to airports comprise a dis-amenity effect on property value, alternatively, the lowest priced properties perceive adjacency to the airport as a positive amenity.

With regard to Wellington region (Table 5), the conditional mean estimate showed a negative pricing effect of 2.22%. However, further analysis across the quantiles of the price distribution reveals that higher priced housing display a much larger negative effect with proximity to the airport. Indeed, examining the pricing impact across the quantiles shows there to be a negative pricing effect of 1.1% at the lowest quantile which increases linearly and marginally to the sixth quantile ($t = 0.6$) exhibiting a negative pricing effect of 2.0%. Higher priced properties then reveal a more pronounced negative pricing effect, ranging from 2.4% at the seventh quantile to 4.2% at the highest quantile (tau = 0.9) of the price distribution. The findings show that whilst there is a negative impact for proximity to airport this is more pronounced for higher priced properties relative to lower priced properties.

Examination of the Christchurch region (Table 6) reveals contrasting findings relative to Auckland and Wellington. The conditional mean coefficient indicated that there is a positive but small pricing effect of 0.7%. The quantile analysis however shows there to be a higher positive pricing effect for higher-priced housing (tau = 0.9) proximal to the airport of 0.9%. This effect gradually decreases when moving down the quantiles, with a negative pricing effect of 0.4% notable for the lowest quantile (tau = 0.1). With respect to Queenstown (Table 7), the findings

Table 5. Quantile regression regional models (Wellington).

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
Constant	18.3156***	17.11736***	16.44149***	16.12905***	16.17808***	16.40081***	16.62664***	16.66522***	16.96718***
Size (m^2)	0.002394***	0.00264***	0.002758***	0.00289***	0.003054***	0.003282***	0.003461***	0.003603***	0.0038***
Age	−0.00273***	−0.00207***	−0.00169***	−0.00151***	−0.00151***	−0.00161***	−0.00168***	−0.00162***	−0.00167***
Dis Airport	−0.01114***	−0.01441***	−0.0161***	−0.01661***	−0.01784***	−0.01951***	−0.02431***	−0.03162***	−0.04212***
Baths 2	0.084645***	0.08719***	0.086306***	0.091136***	0.096272***	0.100419***	0.10407***	0.097748***	0.104761***
Baths 3	0.078846***	0.12888***	0.152048***	0.159284***	0.166971***	0.175667***	0.173193***	0.17518***	0.182228***
Baths 4	−0.08386*	−0.08743	0.055138	0.083725**	0.11471**	0.170832***	0.207621***	0.202745***	0.196543***
Baths 5	−0.0535	−0.34921***	0.117168	−0.04285	0.301996***	0.185839**	0.162975	0.20212***	0.144754**
Beds 1	−0.68249***	−0.55445***	−0.5126***	−0.42778***	−0.36976***	−0.3101***	−0.29431***	−0.28823***	−0.27868***
Beds 2	−0.18812***	−0.15952***	−0.13859***	−0.11304***	−0.08524***	−0.0638***	−0.05286***	−0.05184***	−0.05673***
Beds 4	0.02049**	0.02955***	0.02944***	0.03844***	0.03527***	0.04049***	0.032658**	0.02753***	0.03492***
Beds 5	0.0353**	0.04994**	0.05348***	0.0518***	0.05608***	0.07657***	0.06574***	0.05414***	0.07736***
Beds 6	0.0924	0.12344***	0.14116***	0.11462**	0.12212***	0.11798***	0.11205**	0.05624	0.06709
Suburbs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.428148	0.411339	0.404939	0.403321	0.405812	0.410737	0.416887	0.418356	0.407249
Adj. R^2	0.425598	0.408715	0.402286	0.400661	0.403163	0.40811	0.414287	0.415763	0.404606
S.E. of regress.	0.487686	0.390905	0.351925	0.330539	0.324611	0.330783	0.349311	0.388225	0.465655
Quantile depen.	13.04332	13.27251	13.4	13.49874	13.59237	13.68654	13.79531	13.95961	14.15555
Sparsity	1.205558	0.742482	0.580899	0.516769	0.505097	0.508415	0.587884	0.73833	1.098933
Prob(QuasiLR)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	15,358	15,358	15,358	15,358	15,358	15,358	15,358	15,358	15,358

"*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level respectively. Parsimonious models are presented. Location and time dummy variables available upon request. Suburbs totalled 54 for Auckland; 56 for Wellington; 32 for Queenstown and 94 for Christchurch. Quarterly time periods: Q1,2018-Q1,2022. VIF and Tolerance statistics available upon request. Huber Sandwich Standard Errors & Covariance. Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall Sheather.

Table 6. Quantile regression regional models (Christchurch).

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
Constant	13.0476	12.79029	12.81083	12.5987	12.55207	12.71689	12.79749	13.30205	13.44714
Size (m^2)	0.002186***	0.002513***	0.002661***	0.002911***	0.002931***	0.003195***	0.003373***	0.003619***	0.003775***
Age	−0.00018**	−5.55E−05	−6.65E−05	6.03E−05	0.000103	3.26E−05	1.26E−05	−0.00024**	−0.00027**
Dis Airport	−0.00444*	0.001193**	0.004315**	0.004536***	0.005426***	0.005291***	0.00534***	0.007169***	0.008636***
Beds 1	−0.094686***	−0.07784***	−0.15885***	−0.20659***	−0.27264***	−0.29775***	−0.37519***	−0.41292***	−0.50623***
Beds 2	−0.00799**	−0.01455*	−0.01132*	−0.01679*	−0.02835***	−0.02239***	−0.03736***	−0.04306***	−0.04388***
Beds 4	0.010778*	0.009107*	0.011385**	0.002318	0.000674	0.00667*	0.01394***	0.02854***	0.03136***
Beds 5	0.01211	−0.01442	−0.00788*	−0.02816**	−0.03061***	−0.04224***	−0.05167***	−0.05118***	−0.034**
Beds 6	0.09368	0.18704**	0.03184	0.01452	0.08264***	0.05956	0.05164	0.15067***	0.083968**
Baths 2	0.011143**	0.014049**	0.018434***	0.010698**	0.0072	0.003891	−0.0022	−0.00274	−0.02993***
Baths 3	0.013357*	0.068053***	0.074311***	0.073299***	0.067601***	0.064135***	0.073363***	0.063352***	0.035004**
Baths 4	0.003674	0.099855**	0.101539***	0.128194***	0.145483***	0.131507***	0.150645***	0.164431***	0.059418
Baths 5	0.026018	−0.04596	0.206325***	0.148984***	0.232129***	0.225225***	0.460384***	0.498336***	0.230294***
Suburbs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.37652	0.330314	0.310651	0.324173	0.35161	0.386416	0.419108	0.447714	0.46741
Adjusted R2	0.372718	0.32623	0.306447	0.320052	0.347657	0.382675	0.415565	0.444346	0.464162
S.E. of regression	0.54246	0.461133	0.381285	0.364066	0.360333	0.368201	0.383739	0.412765	0.467232
Quantile depen.	12.83468	13.0919	13.20854	13.30468	13.3739	13.44734	13.54763	13.68768	13.99783
Sparsity	1.092181	0.665089	0.569337	0.478474	0.422538	0.387024	0.411831	0.526209	0.892662
Prob(Quasi-LR)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

"*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level respectively. Parsimonious models are presented. Location and time dummy variables available upon request. Suburbs totalled 54 for Auckland; 56 for Wellington; 32 for Queenstown and 94 for Christchurch. Quarterly time periods: Q1,2018-Q1,2022. VIF and Tolerance statistics available upon request. Huber Sandwich Standard Errors & Covariance. Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall Sheather.

reveal differences between higher and lower priced properties and adjacency to the airport. Higher-priced properties show a tendency towards negative externalities associated with proximity to the airport, reflected in a pricing coefficient of – 0.02% at $\tau = 0.9$. On the other hand, lower-priced properties demonstrate a positive pricing effect of 0.02% with increasing distance from the airport. When comparing Queenstown's results with those of the other three cities, the effect of distance from the airport on various housing price tiers appears less pronounced. The coefficients for Dis Airport are generally smaller in magnitude and exhibit less variability across the different housing categories.

Lastly, we have conducted an extensive series of robustness checks to account for potential sources of statistical bias, including omitted variable bias,

Table 7. Quantile regression regional models (Queenstown).

Variable	q10	q20	q30	q40	q50	q60	q70	q80	q90
Constant	28.12601***	20.85661***	19.86873***	19.88006***	20.18877***	21.87069***	24.10394***	25.40821***	29.44401***
Size (m^2)	0.004272***	0.004252***	0.004161***	0.004283***	0.004552***	0.004751***	0.004816***	0.005124***	0.005472***
Age	−0.00775***	−0.00397**	−0.00343**	−0.00342**	−0.00358***	−0.00441***	−0.0055***	−0.00613***	−0.00809**
Dis Airport	0.000211**	0.000590**	−0.000554**	−5.11E−05**	−3.53E−05**	−2.83E−05*	−5.24E−05**	−6.56E−05**	−0.00023***
Baths_1	−0.055169**	−0.000354**	−0.00772***	−0.01377**	−0.00443***	−0.00518***	−0.003949***	−0.039074**	−0.062217**
Baths_3	0.08235***	0.07606**	0.020389***	0.029443**	0.056141**	0.053857**	0.069163**	0.090122**	0.203353*
Baths_4	0.06396*	0.05714**	0.035283***	0.116197**	0.129345**	0.125417**	0.233368**	0.282444**	0.236206**
Baths_5	0.01895*	0.01013	0.03076***	0.064952*	0.10419*	0.156504**	0.185996*	0.255617*	0.201896***
Beds_1	−0.09618**	−0.15643**	−0.15803**	−0.14318***	−0.13944***	−0.12233***	−0.11312**	−0.13314**	−0.06695*
Beds_2	−0.08178***	−0.05856***	−0.04545**	−0.02994	−0.01306***	−0.018424**	−0.037342**	−0.036268**	−0.0582
Beds_4	0.02238**	0.0543**	0.03157***	0.03188**	0.04286**	0.04362**	0.0402**	0.03347***	0.09453**
Beds_5	0.16179*	0.1417**	0.13506*	0.10799*	0.11903***	0.12484	0.10283***	0.11915**	0.19593**
Beds_6	0.12979	0.1173	0.05301	0.11728	0.19556**	0.24293**	0.23521**	0.22029**	0.41738**
Suburbs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.326465	0.282218	0.295434	0.327169	0.355758	0.374565	0.386766	0.397463	0.399951
Adjusted R2	0.3195	0.274795	0.288148	0.320211	0.349096	0.368097	0.380424	0.391232	0.393746
S.E. of regression	0.71789	0.553327	0.47182	0.454322	0.456996	0.463571	0.484725	0.529418	0.638717
Quantile depen.	13.13231	13.44445	13.59237	13.70458	13.8105	13.95961	14.09692	14.28551	14.62644
Sparsity	1.927518	1.17964	0.730418	0.579906	0.536295	0.591605	0.690603	0.94569	1.628137
Prob(Quasi-LR stat)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

"*", "**" and "***" indicate statistical significance at the 10%, 5% and 1% level respectively. Parsimonious models are presented. Location and time dummy variables available upon request. Suburbs totalled 54 for Auckland; 56 for Wellington; 32 for Queenstown and 94 for Christchurch. Quarterly time periods: Q1,2018-Q1,2022. VIF and Tolerance statistics available upon request. Huber Sandwich Standard Errors & Covariance. Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall Sheather.

model misspecification, and endogeneity.[2] The methodology and results of these tests are detailed in the Appendices A1-A4. In summary, the robustness checks yield results that are broadly consistent with our main findings in terms of the direction, magnitude, and statistical significance of the key variables under investigation.

V. Discussions

The findings stemming from this study highlight the complexity and heterogeneity in the linkage between house prices and proximity to airports across different urban areas in New Zealand. These variations in effect can be explained through the lens of economic theories and echo empirical research findings in the housing literature, and could reflect the distinct economic structures, geographical constraints and housing market dynamics of each studied city.

First, the positive distance decay effect observed in Auckland and Christchurch can be understood through the theory of urban amenities and dis-amenities. Proximity to airports is seen as a positive amenity for lower-priced properties in Auckland, likely due to better accessibility and the resultant reduced travel costs for residents who might prioritize convenience given their income or wealth constraints. As New Zealand's main commercial and population centre, Auckland has traditionally higher property prices and greater demand pressure, making accessibility particularly important for cost-sensitive households. Conversely, in high-priced suburban areas, residents may be more sensitive to any perceived environmental dis-amenities. As a result, the negative impact of airport proximity is statistically significant. This aligns with the theory that higher-income households value tranquillity and environmental quality more than accessibility to urban infrastructure and amenities. This dichotomy suggests a trade-off between accessibility and quality of life across the income/wealth spectrum, as posited by Brueckner et al. (1999) in their examination of urban economic theory.

In Wellington, the negative externality arising from airport proximity for higher-priced housing indeed supports the concept of environmental dis-amenities in urban economics (e.g. M. J. Mccord et al. 2018; Won Kim, Phipps, and Anselin 2003). Noise pollution, increased traffic, and potential safety concerns associated with airport proximity can detract significantly from the desirability of higher-priced homes. This is in line with findings

[2]We are grateful to the two anonymous reviewers for their constructive comments concerning the robustness of our statistical models. One reviewer specifically recommended further verification of the assumptions underlying linear distance decay and monocentric urban structure. The other highlighted potential concerns regarding endogeneity and reverse causality between house prices and the explanatory variables.

by Nelson (2004), who observed that noise pollution from airports can substantially diminish property values in affluent neighbourhoods, where inhabitants place a higher premium on peace and environmental attributes. Consequently, the marked negative impact on Wellington's higher-priced properties underscores the value these residents place on environmental tranquillity.

As a service-based economy with a relatively small urban footprint and high population density, Wellington's land constraints further intensify the proximity effects of airport-related noise and congestion.

In Queenstown, the nominal but positive pricing effect for lower-priced properties and the negative effect for higher-priced properties suggest a blend of accessibility benefits for the former and dis-amenity effects for the latter. This region's unique economic reliance on tourism might explain the lower-tier housing's positive response to airport proximity, as it provides crucial accessibility for tourists and tourism workers. Queenstown's spatial isolation and reliance on aviation also mean that alternatives for inter-regional access are limited, making airport access a necessity for tourism workforce but a burden for affluent homeowners seeking exclusivity. For higher-tier properties, the environmental costs and potential congestion associated with airport proximity seem to outweigh these benefits. The luxury residential market in Queenstown is indeed predominately driven by buyers who prioritize exclusivity, tranquillity, and the town's scenic beauty. Consequently, the negative impact of airport proximity on these properties is significant, as it disrupts the serene environment that these buyers value. Additionally, zoning regulations in Queenstown are strict due to environmental preservation goals, potentially limiting the housing supply response and further increasing the premium placed on quiet, remote locations. This phenomenon is consistent with the urban economics theory of Tiebout (1956) that conjectures individuals are prone to 'vote with their feet' to choose residential locations that best fit their preference for public goods, amenities and economic externalities.

Christchurch presents an interesting case where high to medium-priced properties near the airport experience a positive pricing effect. This could be attributed to the specific economic structure and urban layout of the city, where the benefits of accessibility and economic opportunities associated with proximity to the airport outweigh the dis-amenity effects. This aligns with the findings of Ihlanfeldt and Taylor (2004), who suggest that in some urban contexts, the economic benefits of proximity to key infrastructure can supersede potential dis-amenities, especially in areas with significant commercial or tourism activities. A closer examination of Christchurch's geography reveals that the city centre is a mere 8 kilometres from Christchurch International Airport, fostering business opportunities for high-price to medium-priced properties. This proximity facilitates ventures such as short-term letting or other tourism-related enterprises between the airport precinct and the city centre, thus elucidating why airport proximity constitutes a positive amenity for a large cross-section of the sample properties. Moreover, the predominant high value neighbourhoods close to the airport were also relatively less affected by the 2011 earthquakes, given the geology of the land near the airport. There is also a unique regulatory control, where Christchurch Airport's 24 hour curfew free fly zone (i.e. noise abatement rather than noise curfew) is maintained, by ensuring housing development activity surrounding the airport is limited. Additionally, post-earthquake recovery has spurred significant development and population growth in Christchurch, enhancing the value of accessible locations like those near the airport. The strict limitation on residential development immediately surrounding the airport, enforced to maintain its operational freedom, paradoxically preserves the amenity value and reduces noise exposure for the existing higher-value properties just beyond this zone, contributing to their positive pricing response.

Overall, the use of quantile regression techniques further elucidates the differential impacts across different property price distributions, highlighting that lower-priced properties are generally more positively influenced by proximity to airports compared to higher-priced properties. This can be explained through the theory of marginal utility of income, where lower-income households tend to derive a greater amount of utility from the reduced travel costs and increased accessibility afforded by proximity to airports, as opposed to higher-income households who are more likely to experience diminishing marginal utility from these benefits (Mankiw and Taylor, 2020). However, as demonstrated by the contrasting city-level results, this general pattern is significantly mediated by local context, such as the city's economic base, spatial form, regulatory environment, and historical events.

VI. Conclusion

This study empirically corroborates and expands upon existing research in housing economics and real estate valuation, emphasizing the multifaceted and locally contingent impacts of airport proximity on home prices. In traditional hedonic pricing literature, airport proximity is often perceived negatively due to the associated air and noise pollution, particularly when high-tier real estate is concerned. This negative perception is typically counterbalanced by the reduced transportation costs resulting from greater convenience, which is especially beneficial for low-income households whose utility functions tend to favour cost-saving measures. Against this backdrop, our study aims to empirically examine these opposing forces and argue that the local spatial configuration of the city and its economic characteristics should be considered when assessing the effect of airport proximity on property pricing tiers.

Utilizing quantile hedonic regression methods, our research reveals that properties of different tiers respond differentially to proximity to airports. Specifically, whilst noise-related factors and environmental externalities from airport operations can negatively impact property pricing, proximity to airports can be a value-enhancing attribute for medium to high-tier properties in certain New Zealand cities (e.g. Christchurch) where 'inter-alia' property development has been curtailed to meet no curfew flying freedoms for aviation activity. We posit that this phenomenon is attributed to the increased value these properties gain from access to quality peri-urban suburban neighbourhoods, due to restricted housing development near the airport, and due to these neighbourhoods having resilience (more stable geology) from the 2011 major earthquake.

This subtle market dynamic is often overlooked by property valuers, who typically assume accessibility to urban infrastructure has a uniform impact on home prices across the spectrum of property pricing tiers. Highlighting this aspect can provide valuable insights for real estate valuation, particularly concerning compensating property owners due to relocation arising from airport and urban infrastructure development/redevelopment projects. For instance, traditional wisdom and empirical evidence seem to suggest that the construction of a new airport typically decreases property values due to noise and air pollution. However, our study empirically confirms that in certain contexts, and we stress in certain contexts, that airport proximity can positively influence property values even for high-end real estate.

For future research, we suggest empirically exploring the interplay between transportation costs, housing supply and demand dynamics, tourism, and the spatial distribution of real estate, utilizing granular geo-referenced data to enhance accuracy and robustness. This could be examined in conjunction with environmental data, socioeconomic attributes as well as property-level information such as house types (e.g. single family detached versus townhouse versus apartment) and land use permissions. Furthermore, conducting similar studies in other countries and cities with comparable spatial and economic settings to New Zealand could empirically confirm and further explore the subtle pricing effects of airport proximity discussed in this paper.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A. Robustness Tests

To enhance the reliability of our empirical analyses, we construct and estimate several robustness models employing alternative specifications to mitigate potential biases arising from omitted variables, model misspecification and endogeneity.

Firstly, our baseline models posit a linear geographical impact of airport proximity on house prices. However, extant literature indicates that neighbourhood characteristics and other spatial or amenity attributes may exert non-linear influences on property values (M. J. Mccord et al. 2018, M. Mccord et al. 2020 and M. Mccord et al. 2022). Consequently, we devise supplementary models for the four New Zealand housing submarkets incorporating an exponential distance specification to capture the spatial decay in the airport's effect—an approach that arguably better reflects reality. Secondly, recognising the multifaceted nature of urban

Table A1. Robustness models (Auckland).

Variable	q10	q30	q50	q70	q90
Constant	5.688558***	0.000000***	0.000000***	0.000000***	5.980732***
SIZE (m2)	0.001565***	0.001686***	0.001825***	0.001829***	0.001810***
Age	0.001456***	0.001473***	0.001473***	0.001427***	0.001351***
Dis Airport (exp)	0.000013***	0.000007***	0.000006***	0.000002***	−0.000001***
Dis CBD (exp)	0.000001***	0.000001***	0.000000***	0.000001***	0.000003***
Beds 1	−0.245326***	−0.232588***	−0.225165***	−0.229401***	−0.224474***
Beds 2	−0.083508***	−0.088811***	−0.089576***	−0.085818***	−0.074686***
Beds 4	0.025302***	0.021283***	0.013512***	0.005579***	0.012890***
Beds 5	0.011597***	0.006035***	−0.014931***	−0.019948**	−0.021777***
Beds 6	−0.055809***	−0.040120	−0.066482***	−0.080982***	−0.073669***
Baths 2	0.004445***	−0.003182***	−0.000193***	0.004566***	−0.006523***
Baths 3	0.019681***	0.006168	0.005954**	0.009135***	−0.001354***
Baths 4	0.038630*	0.021198***	0.022631***	0.027731***	0.036611***
Baths 5	0.024178***	0.013975***	−0.024494***	−0.008320***	−0.056953***
Suburbs	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.515908	0.557472	0.554791	0.546496	0.527191
Adj. R2	0.513837	0.555578	0.552886	0.544556	0.525167
S.E. of reg.	0.188849	0.142045	0.128468	0.139402	0.199135
Quantile depen.	5.845098	6.021189	6.164353	6.295567	6.498311
Sparsity	0.537528	0.276385	0.258174	0.297035	0.649494
Prob (Quasi-LR)	0.000	0.000	0.000	0.000	0.000
No. Obs	9388	9388	9388	9388	9388

'*', '**' and '***' indicate statistical significance at the 10%, 5% and 1% level respectively.

Table A2. Robustness models (Wellington).

Variable	q10	q30	q50	q70	q90
Constant	0.000000***	0.000000***	12.88877***	0.000000***	0.000000***
Size (m2)	0.002364***	0.003304***	0.003351***	0.003556***	0.004034***
Age	−0.002504***	−0.002034***	−0.001895***	−0.001957***	−0.002044***
Dis Airport (exp)	−0.000079***	−0.000003***	−0.000004***	−0.000005***	−0.000007***
Dis CBD (exp)	0.000021***	0.000011***	0.000023***	0.000009***	0.000008***
Baths 2	0.109843**	0.083223***	0.085196***	0.090949***	0.101120***
Baths 3	0.202542***	0.164928**	0.173256***	0.174122***	0.181127***
Baths 4	0.102610***	0.026612***	0.075576***	0.132198***	0.124919***
Baths 5	0.194818***	0.216985***	0.113423***	0.069686**	0.383574***
Beds 1	−0.610236***	−0.361741***	−0.276418**	−0.277342***	−0.259765***
Beds 2	−0.164104***	−0.133321***	−0.104691***	−0.073147***	−0.057415***
Beds 4	−0.025905***	−0.042237***	−0.036447***	−0.026101***	−0.023522***
Beds 5	−0.066140**	−0.098028***	−0.069425***	−0.058014***	−0.073306**
Beds 6	−0.047151***	−0.164325***	−0.153225***	−0.063815***	−0.070739***
Suburbs	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.436733	0.436795	0.445912	0.468581	0.460317
Adj. R2	0.432692	0.432753	0.441937	0.464768	0.456444
S.E. of regress.	0.469842	0.349737	0.326373	0.349308	0.432894
Quantile depen.	13.05001	13.42247	13.61462	13.82249	14.20586
Sparsity	1.189183	0.616636	0.499134	0.548570	0.957607
Prob(QuasiLR)	0.000	0.000	0.000	0.000	0.000
No. Obs	7721	7721	7721	7721	7721

'*', '**' and '***' indicate statistical significance at the 10%, 5% and 1% level respectively.

Table A3. Robustness models (Christchurch).

Variable	q10	q30	q50	q70	q90
Constant	12.45226***	0.000000***	0.000000***	0.000000***	0.000000***
Size (m^2)	0.002334***	0.002671***	0.002935***	0.003298***	0.003863***
Age	−0.000177***	−6.63E−05***	−0.000310***	0.000012***	−0.000102***
Dis Airport (exp)	−0.000003***	0.000014***	0.000017***	0.000004***	0.000032***
Dis CBD (exp)	3.82E−33***	0.000002***	1.50E−31***	1.51E−31***	0.000001***
Beds 1	−0.326848***	−0.236411***	−0.226962***	−0.174294***	0.232036***
Beds 2	−0.117678***	−0.116096***	−0.115093***	−0.091019***	−0.053527***
Beds 4	0.051954*	0.058727***	0.036846***	0.020736***	0.001327***
Beds 5	0.075280***	0.037296***	0.006228***	−0.009917***	0.007563***
Beds 6	0.024499***	0.023576**	−0.008976***	0.044131***	0.276211***
Baths 2	0.054374***	0.055473**	0.058922***	0.051760***	0.050026***
Baths 3	0.067479***	0.115223***	0.131183***	0.147984***	0.134397***
Baths 4	0.077812**	0.174989***	0.251761***	0.291112***	0.218517***
Baths 5	0.014604**	−0.017537***	0.166925***	0.312960***	0.537261***
Suburbs	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.347490	0.349393	0.423525	0.475994	0.511850
Adjusted R2	0.345040	0.346950	0.421361	0.474027	0.510017
S.E. of regression	0.533169	0.353954	0.339162	0.356945	0.442101
Quantile depen.	12.74549	13.03898	13.22130	13.42985	13.86620
Sparsity	1.052271	0.523188	0.388315	0.420726	0.912990
Prob(Quasi-LR)	0.000	0.000	0.000	0.000	0.000
No. Obs	13637	13637	13637	13637	13637

'*', '**' and '***' indicate statistical significance at the 10%, 5% and 1% level respectively.

Table A4. Robustness models (Queenstown).

Variable	q10	q30	q50	q70	q90
Constant	0.000000***	0.000000***	13.03287***	0.000000***	0.000000***
Size (m2)	0.003254***	0.003708***	0.004117***	0.004400***	0.005126***
Age	−0.000837***	−0.001308***	−0.002081***	−0.004327***	−0.000629***
Dis Airport (exp)	0.000008***	−0.000003***	−0.000001***	0.000000***	−0.000001***
Dis CBD (exp)	0.000000***	0.000000***	0.000000***	0.000000***	7.28E−06***
Baths_1	−0.260423***	−0.162947***	−0.158103***	−0.214675***	0.011706***
Baths_3	0.096158***	0.065376***	0.056246***	0.015016***	0.050021***
Baths_4	0.089758***	0.054320***	0.021139**	−0.018963***	−0.052715***
Baths_5	0.020935***	−0.116216***	−0.043196***	−0.052534***	−0.122067***
Beds_1	0.057769***	−0.042261***	−0.030551***	−0.042383***	−0.061374***
Beds_2	0.088975***	−0.014067***	−0.023131***	−0.048111***	−0.097896***
Beds_4	0.000295***	0.073475***	0.104646***	0.105003***	0.128340***
Beds_5	−0.401846***	−0.262843***	0.013603***	−0.056233***	0.103853***
Beds_6	−0.411743***	−0.105965***	−1.000887***	−0.394696***	−0.692435***
Suburbs	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.384738	0.326900	0.378106	0.400713	0.413821
Adjusted R2	0.374080	0.315241	0.367334	0.390333	0.403667
S.E. of regression	0.729481	0.498718	0.480388	0.504435	0.900651
Quantile depen.	13.13231	13.59934	13.81551	14.07787	14.60397
Sparsity	1.212186	0.587040	0.465377	0.585209	1.490892
P(Quasi-LR stat)	0.000	0.000	0.000	0.000	0.000
No. Obs.	2409	2409	2409	2409	2409

'*', '**' and '***' indicate statistical significance at the 10%, 5% and 1% level respectively.

economic nodes, we integrate an additional centre of economic activity—the central business district (CBD)—alongside the airport node. This multi-node spatial framework enables comparison against the original mono-node assumption (Lo, Chau, et al. 2022, Lo, Liu, et al. 2022 and M. Mccord et al. 2024). Analogous to the airport specification, the CBD variable is modelled via an exponential distance function. Thirdly, we address selection bias stemming from unobserved heterogeneity, whereby dwellings in noise-affected areas may systematically differ from those in quieter locales. For instance, properties in tranquil neighbourhoods often benefit from amenities such as well-maintained gardens or extensive landscaping—features that are less valued adjacent to airports due to noise disturbance. Consequently, part of the observed price discount associated with airport proximity may reflect these unobserved attributes rather than noise per se.

Table A5. Instrumental variable models.

Variable	Auckland	Wellington
Constant	5.980732***	12.40851***
Size (m2)	0.001810***	0.002866***
Age	−0.001359***	−0.002191***
Dis Airport	0.064483***	−0.024098***
Dis CBD	0.000071***	0.000148***
Baths_1	0.003705	NA
Baths_2	NA	0.113005***
Baths_3	−0.018066***	0.171502***
Baths_4	−0.049867***	0.116638***
Baths_5	−0.161672***	0.185860**
Beds_1	−0.241022**	NA
Beds_2	−0.082908***	0.291644***
Beds_3	NA	0.398778***
Beds_4	−0.015907***	0.366183***
Beds_5	−0.070488***	0.339606***
Beds_6	−0.143821***	NA
Suburbs	Yes	Yes
Time	Yes	Yes
R2	0.704154	0.608314
Adjusted R2	0.703640	0.606201
S.E. of regression	0.192926	0.304596
F Statistic	1370.026	287.8733
Prob(F-Stat)	0.000000	0.000000
Second-Stage SSR	599.8814	1392.978
Instrument rank	50	82
No. Obs	16146	5096

'**' and '***' indicate statistical significance at the 5% and 1% level respectively.

To account for potential selection bias, we adopt a two-stage approach incorporating propensity score matching (PSM). In the first stage, we estimate a baseline model that includes airport-distance dummy variables, enabling us to identify "treated" locations—defined as those where the estimated effect of airport proximity exceeds the sample mean. These treated observations are flagged using a binary indicator. In the second stage, we use this treatment indicator to construct a matched sample via PSM, aligning treated and control observations on observable characteristics. We then re-estimate the original model on the matched sample to assess whether the key estimates remain robust or differ materially from those obtained using the full sample.

Tables A1-A4 present the results of the robustness checks for the four New Zealand housing submarkets, incorporating all the aforementioned model enhancements. For conciseness, we report only the estimated coefficients for the 10th, 30th, 50th, 70th, and 90th quantiles.

The results demonstrate that the effect of airport proximity remains broadly consistent with the baseline models in terms of the sign and direction of the key variables. Notably, the estimated coefficients for distance to airport under the exponential distance specification are substantially smaller in magnitude than those derived from the original linear models, highlighting a pronounced spatial decay effect.

In addition, the influence of proximity to the central business district (CBD) is found to be predominantly positive—or at least non-negative in the case of Queenstown—aligning with established findings in the housing literature. These results suggest that, within the New Zealand context, the CBD constitutes a valued spatial amenity, with the advantages of urban accessibility and service concentration outweighing potential disamenities such as congestion, noise, or pollution.

Furthermore, there exists the possibility of reverse causality whereby house prices may influence the location or expansion of airports. For instance, airports may be constructed or extended in areas where land values are relatively low, or where development plans are shaped by prevailing patterns of economic activity and real estate dynamics. This reverse relationship introduces a potential source of endogeneity into the estimation of proximity effects. To address this concern, we develop and estimate two additional robustness models for the Auckland and Wellington housing markets, employing an instrumental variables (IV) approach. Specifically, we utilise instruments that are correlated with airport proximity but are exogenous to current house prices.

In our specification, we adopt proximity to historical or proposed airport sites as the instrumental variable. For the Auckland market, we employ proximity to Whenuapai Airport—a former civil airport—as the instrument, flagging properties within a 20-kilometre radius with a binary indicator. This catchment includes properties in the districts of Kingsland, Epsom, Mount Eden, Grey Lynn, Wesley, Westmere, Sandringham, Point Chevalier, and Three Kings. For Wellington, we use proximity to Paraparaumu as the instrument, a location historically proposed for airport development and considered a viable site in earlier planning frameworks. Analogously, we identify proximate districts such as Northland, Thorndon, Karori, Pipitea, Wilton, Wadestown, Mount Victoria, Kaiwharawhara, Crofton Downs, Khandallah, Broadmeadows, and Newlands. The estimation results for the IV models are presented in Table A5. An examination of the direction, magnitude, and statistical significance of the key variables reveals that the findings remain broadly consistent with those obtained from the original quantile regression models. In particular, the coefficient on airport proximity is positive and statistically significant at the 1% level for Auckland, whereas it is negative and also significant at the 1% level for Wellington. These results reinforce the robustness of our empirical strategy and lend further support to the observed spatial heterogeneity in the effect of airport proximity across different urban markets.