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Measuring Quality-Adjusted House Prices across Time and Space

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Measuring Quality-Adjusted House Prices across Time and Space*

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Abstract

We develop new measures of quality-adjusted house prices that can be used to compare housing costs across different locations and different points in time. The proposed measures, which we call fixed attribute house prices (FAHPs), permits users to make more informed judgements about the price of housing in different locations by holding housing attributes such floorspace, land area and proximity to employment fixed when making comparisons between different urban areas. The measure is based on hedonic regressions that permit the price of housing attributes to vary between different locations and time periods of interest. The estimated hedonic functions can then be used to price a dwelling with identical attributes in these different locations and at different points in time. The measure can therefore account for compositional shifts in transacted properties over time that can distort price measures based on median or arithmetic averages of sales prices. But, unlike repeat sales methods, it can also account for compositional differences between housing in different regions. We showcase the method by comparing the costs across the different urban centres to purchase a house with the median attributes of the country's urban housing stock. Currently in Auckland, New Zealand's most expensive city, a house with the NZ median attributes cost 21-29% more than the recorded median sales value in the region. Controlling for the attributes of the housing stock suggests that Auckland housing is more expensive than the dollar amount implied by the conventional median sales price. Intuitively, Auckland housing is, on average, smaller and requires longer commutes than houses in other urban centres, and thus its housing stock is more expensive once its lesser quality is accounted for.

Keywords: House Prices, Hedonic Imputation Price Index, House Prices.

JEL Classification: R31, E31.

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1 Introduction

House prices and housing costs are an important component of the cost of living. However, accurate measurement of house prices and housing costs is significantly complicated by the inherent heterogeneity of the housing stock. Unlike many other goods and services available to consumers, houses frequently exhibit substantial variation in attributes such as floorspace, land area and access to locations of employment. Making comparisons of housing costs across different regions and time periods is difficult because housing attributes vary between the individual houses transacted, making like-for-like comparisons of prices across time and space impossible.

Conventional approaches to measuring house prices, such as repeat sales and hedonic imputation indexes, address the measurement problems caused by heterogeneity in the housing stock by holding the individual attributes of the transacted houses fixed. The repeat sales method does this by tracking the price of individual houses over time, under the assumption that the attributes of the individual houses are unchanged between sales. Hedonic methods of price measurement conceptualise houses as a bundle of attributes, with different houses varying in their respective endowments of these distinct attributes. Hedonic imputation methods price these endowments using fitted regressions, which enables prediction (or imputation) of individual house prices in periods when they are not transacted.

However, both repeat sales and the extant hedonic methods are used to measure time series variation in house prices, meaning that these methods cannot be used to assess differences in the price of housing between different regions. Spatial price differentials are useful for households and firms making locational decisions. Constructing house price indexes that facilitate comparisons between different regions is complicated by diversity in housing composition and patterns of urban development between locations. Housing in a more populous city is likely to have smaller living spaces and longer commute times, on average, than housing in a less populous city. Relying on differences in some measure of average prices between the two cities is therefore likely to understate the comparative cost of living in the more populous city because its housing stock is of lesser quality. Adjusting for the differences in the attributes of the housing stock in different locations is critical to understanding differences in the cost of living between different locations.

In this paper we propose a new measure of house prices that facilitates comparisons across time and across different regions. The measure extends hedonic approaches that hold housing attributes fixed when measuring house prices. The basic idea is to fit a hedonic function to transacted house prices in each time period and in each region of interest. We then take a house with fixed attributes and price the house in each region and in each time period using the fitted hedonic function. We refer to the measure as fixed attribute house prices (FAHP). Housing attributes can be fixed at any level specified by the user. We illustrate the measure by fixing attributes at the median endowment for the housing stock across all urban regions of analysis. We refer to this as the median attribute house.

Our method builds on and contributes to the vast literature on house price measurement. Many of these methods are designed to hold housing quality constant when measuring price growth, such as the commonly-used repeat sales indexes (Bailey et al., 1963; Case and Shiller; 1987; Case et al., 1991) and sales price appraisal ratio (SPAR) methods (Bourassa et al. 2006). However, because these indexes measure time series variation in price growth, they cannot be used to compare differences in house prices between different locations. Hedonic methods can also be used to construct constant quality house price indexes (Hill, 2013). Silver (2016) refers to hedonic methods as the "gold standard" in constant-quality house price measurement. However, to date these methods have only been used to produce indexes that measure time series variation in prices. We further develop these hedonic methods to build measures of house prices that can be used to make comparisons across time and between locations.

We use a hedonic price measurement method that allows the coefficients on housing attributes to change over time. This is a desirable feature of the model as both the supply and demand of various components of a product bundle are likely to differ over time and between different locations (Pakes, 2003). It also generates improvements in predictive accuracy in individual house prices (Greenaway-McGrevy and Sorensen, 2021). The time-varying hedonic approach differs from the time-dummy hedonic method in that it permits temporal variation in the shadow prices of hedonic characteristics (Hill, 2013). See Silver and Heravi (2007) for a comprehensive review of hedonic imputation and hedonic time dummy index approaches.

To showcase the new measure, we construct FAHPs for the Functional Urban Areas (FUAs) of New Zealand. FUAs are contiguous areas that are defined based on commuting patterns and are analogous to cities and towns. We find that, as of 2020, a dwelling with the median level of attributes (MA) is most expensive in Auckland and least expensive in Gore. The FAHPs also reveal significant differences between median sales prices and what it costs to purchase a house with the median attributes in the different urban areas of New Zealand. In 2020, the median sales price was $930,000 in Auckland. However, it cost $1.2 million to purchase a house with the median attributes. The difference of about 29% is consistent with the fact that houses in Auckland are typically further from employment centres and have less land than houses in other urban areas in the country. Thus, once the lesser quality of the attributes of Auckland's housing stock is accounted for, housing in Auckland is more expensive than the dollar amount implied by the median sales price. In Hamilton and Tauranga, the median sales price is greater than what it costs to purchase a house with the median attributes, and this is consistent with the fact that the houses in these locations are better endowed with floorspace, land and job proximity, compared to other cities.

The remainder of the paper is structured as follows. Section two outlines FAHP construction. Section three applies the method to FUAs in NZ. Section four concludes.

2 Methodology

In this section we introduce the methodology of the FAHP approach. We begin by introducing the conventional time varying hedonic regression. We then show how predicted prices obtained from the fitted regression are used to construct the constant attribute price index.

2.1 Hedonic Regression

We employ a semi-log hedonic regression function to model house prices. This is the standard hedonic specification used in the real estate literature. The log-linear functional form explicitly attaches a non-linear marginal effect of changes in certain attributes on prices (Malpezzi, 2008).

Let $p_{i(t),t}$ denote the logged transaction price of house $i\,(t)$ sold in period t, and let $X_{i(t),t}$ be a vector of characteristics of the house. The regression is of the form

$$p_{i(t),t} = X'_{i(t),t}\beta_t + \varepsilon_{i(t),t}, \tag{1}$$

We use $t = 1, ..., T$ to index the time periods, and $i(t) = 1(t), ..., n(t)$ indexes the cross sections observed in period t. Our empirical application is applied to repeated cross sections of transaction prices so the cross sectional index is dependent on the time period t. Including the t notation in the cross sectional index $i\,(t)$ makes it clear that for all n properties are transacted in period t.

A salient feature of the regression function is that it allows the coefficients on the characteristics of the house to change in each time period hence the coefficients are indexed by t. In addition to estimating the regression function over different time periods we permit these coefficients to vary between different cities. We include a constant in the vector of characteristics $X_{i(t),t}$ to ensure there is a (time-varying) constant for each FUA in the regression function. Because the regressions are separately fitted to each to FUA, this is akin to including region-time fixed effects and accounts for any unobserved factors that are constant for all houses in a FUA in any given time period.

Observable characteristics such as the floor space or land area are included in$X_{i(t),t}$. Locational attributes can also be included, since the value of access to amenities is often capitalized into house prices. Access to employment is a particularly important driver of locational decisions and thus house prices, and it plays a key role in the conventional AMM model of urban development. We also include a measure of weighted average distance to locations of employment within the FUA, based on information on the distribution of jobs across the Statistical Area Units (SAUs) of the FUA. This allows for polycentric patterns of urban development. The measure is used to approximate commuting costs to locations of employment. See the Appendix for details on the construction of this measure.

2.2 Construction of the Fixed Attribute Measure of House Prices

We estimate (1) for each city in the sample. Let j index region $j = 1, \ldots, N$, and let $\left\{\hat{\beta}_{j,t}\right\}_{t=1}^{T}$ denote the estimates of (β_t) obtained from region j. We then use the fitted coefficients to price a house with fixed attributes $\bar{X}$ in each period as follows

$$\bar{p}_{j,t} = \bar{X}'\beta_{j,t}$$

Taking the exponential of $\bar{p}_{j,t}$ then yields the FAHP for region j in time period t and attributes $\bar{X}$. Because the attributes are fixed over time and space, the index can be used to make comparisons of housing costs between different cities and points in time.

For the most part, we use the median values across all FUAs for$\bar{X}$. This reflects the price of a house with the average endowment of measurable housing attributes across all cities and towns within the country. We refer to this as the Median Fixed Attribute House Price, or M-FAHP. Other levels are possible, such as the lower quartile endowment or the upper quartile endowment, resulting in the LQ-FAHP and the UQ-FAHP.

3 Application

In this section we construct FAHPs for the 53 different FUAs in New Zealand over the 1990 to 2020 time period.

3.1 Data

Our dataset consists of sales transactions for New Zealand spanning the period from 1990 to 2020. From these we extract sales prices for the 53 Functional Urban Areas. Because we wish to quantify measurable attributes of the housing stock, rather than those of sales transactions, these data are tabulated for all unique dwellings in the sample of sales transactions.

Throughout the paper, we will refer to a dwelling with the median endowment of attributes as the 'median attribute house'. The median attribute house has 130 square metres of floorspace, three bedrooms, one bathroom, and 601 square metres of land area. It was built 32 years ago, has a deck, no garage, and no appreciable view. It has exclusive land ownership rights and is free-standing (i.e. it is not part of a multi unit structure). Finally, the weighted average distance to employment locations is about 4.8km. The Table also reveals that there is substantial variation around the mean and median measures of central tendency.

Table 1: Summary Statistics: All Sample

	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.74	1	0.44	0	0	0	1	1	1
Land Area (m^2)	555.34	601	484.41	0	0	0	800	1,216	2,300
Floor Area (m^2)	143.20	130	63.10	40	68	100	180	260	337
Number of Beds	3.11	3	0.86	1	2	3	4	5	5
Number of Baths	1.39	1	0.65	1	1	1	2	3	3
Approximate Age (Years)	35.22	32	26.94	0	0	13	51	89	107
Deck Indicator (0=No,1=Yes)	0.55	1	0.50	0	0	0	1	1	1
Number of Internal Garages	0.78	0	0.90	0	0	0	2	2	3
Number of Free-standing Garages	0.60	0	0.83	0	0	0	1	2	3
Distance to Jobs (km)	7.16	4.79	6.83	0.61	1.03	2.36	10.08	21.39	32.99
View Indicator (0=No,1=Yes)	0.27	0	0.44	0	0	0	1	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.19	0	0.39	0	0	0	0	1	1

Notes: The final six columns denote the percentiles of the empirical distribution.

Table 2: Summary Statistics: Metropolitan Area

	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.69	1	0.46	0	0	0	1	1	1
Land Area (m^2)	480.97	519	443.62	0	0	0	716	1,103	2,002
Floor Area (m^2)	144.72	130	65.61	38	60	100	181	270	341
Number of Beds	3.13	3	0.90	1	2	3	4	5	5
Number of Baths	1.44	1	0.69	1	1	1	2	3	4
Approximate Age (Years)	34.75	30	27.09	0	1	12	50	90	108
Deck Indicator (0=No,1=Yes)	0.51	1	0.50	0	0	0	1	1	1
Number of Internal Garages	0.81	0	0.90	0	0	0	2	2	3
Number of Free-standing Garages	0.53	0	0.79	0	0	0	1	2	3
Distance to Jobs (km)	8.94	6.82	7.27	0.75	1.60	3.79	11.61	22.79	34.77
View Indicator (0=No,1=Yes)	0.29	0	0.45	0	0	0	1	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.22	0	0.41	0	0	0	0	1	1

Next we stratify the sample according to population. Statistics New Zealand uses four categories of FUAs, based on their total population: Metropolitan Areas, which are the largest; Large regional centres; Medium regional centres; and Small regional centres, which are the smallest. We also provide descriptive statistics by these four categories in the tables below. Dwellings in the metro areas are, on average, further from the centre of the FUA and have less land compared to houses in large, medium or small regional centres. The housing stock also tends to be more recently built and has a slightly larger floorspace, on average. These observations support the premise that there are significant differences in the housing stock of different urban areas.

3.1.1 Regressors

The dataset includes a large amount of information for each property transaction. It includes sales price (net of chattels), land area, floor area, number of bedrooms and bathrooms, and various other qualitative and quantitative property characteristics. In addition, each transaction is geo-referenced with World Geodetic System (WGS) 1984 coordinates, permitting the estimation of spatial relationships such as distance to known amenities. We use the geocoordinates of the house to calculate the Haversine distance to the centre of the FUA and other employment centres.

Table 3: Summary Statistics: Large Regional Centre

	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.83	1	0.38	0	0	1	1	1	1
Land Area (m^2)	684.95	683	508.71	0	0	471	860	1,414	2,707
Floor Area (m^2)	139.79	121	56.77	55	70	100	170	250	320
Number of Beds	3.08	3	0.77	1	2	3	3	4	5
Number of Baths	1.28	1	0.52	1	1	1	1	2	3
Approximate Age (Years)	39.76	38	25.55	0	2	20	55	90	106
Deck Indicator (0=No,1=Yes)	0.61	1	0.49	0	0	0	1	1	1
Number of Internal Garages	0.71	0	0.89	0	0	0	2	2	3
Number of Free-standing Garages	0.76	1	0.87	0	0	0	1	2	3
Distance to Jobs (km)	3.79	2.69	3.56	0.75	1.09	1.84	4.25	12.76	19.78
View Indicator (0=No,1=Yes)	0.21	0	0.41	0	0	0	0	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.14	0	0.35	0	0	0	0	1	1

Table 4: Summary Statistics: Medium Regional Centre

	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.83	1	0.37	0	0	1	1	1	1
Land Area (m^2)	718.06	728	516.71	0	0	489	926	1,470	2,677
Floor Area (m^2)	140.44	121	57.91	58	70	100	170	251	322
Number of Beds	3.05	3	0.76	1	2	3	3	4	5
Number of Baths	1.27	1	0.53	1	1	1	1	2	3
Approximate Age	39.31	37	26.86	0	1	18	55	92	108
Deck Indicator (0=No,1=Yes)	0.60	1	0.49	0	0	0	1	1	1
Number of Internal Garages	0.73	0	0.89	0	0	0	2	2	3
Number of Free-standing Garages	0.75	0	0.89	0	0	0	1	2	3
Distance to Jobs	2.97	1.79	3.13	0.61	0.88	1.32	2.71	11.21	13.37
View Indicator (0=No,1=Yes)	0.23	0	0.42	0	0	0	0	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.14	0	0.35	0	0	0	0	1	1

Table 5: Summary Statistics: Small Regional Centre

	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.89	1	0.31	0	0	1	1	1	1
Land Area (m^2)	833.37	794	593.97	0	0	602	1,002	1,922	3,503
Floor Area (m^2)	139.27	122	56.68	50	70	100	170	250	316
Number of Beds	3.06	3	0.75	1	2	3	3	4	5
Number of Baths	1.30	1	0.54	1	1	1	2	2	3
Approximate Age	36.28	33	26.14	0	1	15	52	89	107
Deck Indicator (0=No,1=Yes)	0.64	1	0.48	0	0	0	1	1	1
Number of Internal Garages	0.75	0	0.90	0	0	0	2	2	3
Number of Free-standing Garages	0.74	0	0.89	0	0	0	1	2	3
Distance to Jobs	1.97	1.25	2.33	0.17	0.43	0.86	1.85	7.34	11.84
View Indicator (0=No,1=Yes)	0.26	0	0.44	0	0	0	1	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.09	0	0.29	0	0	0	0	1	1

Table 1 provides descriptive statistics on the set of variables used in the hedonic regressions. The set of explanatory variables includes characteristics that are frequently used in the hedonic house price literature. These are: land area, floor area, age of the building, the number of bedrooms and bathrooms, the number of internal garages and external garages, and weighted distance to employment locations ('distance to jobs'). We take the natural log of land area, floor area, distance to jobs, and age. We include dummy indicators for houses that have decks and appreciable views. We also include an indicator of whether the title of the house has exclusive ownership of the underlying land on the title,[1] and whether the dwelling is in a multi-unit structure (which includes units and apartments). This yields a total of twelve variables in the set of explanatory regressors.[2]

The data is also filtered in order to remove poorly coded data and outliers. Observations with sale prices below $\$20,000$ (NZ dollars) and above $\$25,000,000$ are removed along with those listed as having any traits that exceed the following: 500m^2 of floor space, 1 acre of land (4047m^2), 9 bedrooms, 12 bathrooms, 8 internal garages or 6 external garages.[3] Observations listed with missing data in any of the pertinent characteristic vectors are also removed. Finally, observations for sales of a property that occur twice in a single quarterly period are removed to reduce the effect of non arms-length transactions on estimated market prices.[4]

3.2 Price Measures

We consider three different attribute bundles $\bar{X}$ as described below: median, upper-quartile and lower quartile. We begin by focusing on median attributes as they provide a measure of average prices.

Figure 1 exhibits the M-FAHPs for the six metropolitan areas of NZ: Auckland, Hamilton, Tauranga, Wellington, Christchurch and Dunedin. These are the largest cities in NZ. Since the mid 1990s, Auckland has had the highest house prices, followed by Wellington. Since 2015, prices in Hamilton and Tauranga have exceeded those of Christchurch and Dunedin.

Figures 2 exhibits the M-FAHPs for the large regional centres. There is substantial variation in M-FAHPs, with prices in 2020 varying from $300,000 in Invercargil and Whanganui to $500,000 to $600,000 in Kapiti, Nelson and Napier.

Figures 6 and 7 in the Appendix exhibit the M-FAHPs for the medium and small regional centres. For the medium and small regional centres, the hedonic regression (1) is estimated over a two year sample in order to reduce volatility in the index stemming from fewer transactions in regions with a smaller amount of housing.

3.3 Comparison to Median Sales Prices

In New Zealand, the only available measures of price differences between regions are medians or arithmetic averages. For example, the Real Estate Institute of New Zealand (REINZ) reports median prices on a monthly basis.

The criticisms of using an average measure of house prices to infer differences in house prices between different time periods also apply in the cross section. For example, as shown in the Tables above, houses in the metro areas are on average, further from jobs and have less land compared to houses in large, medium or small regional

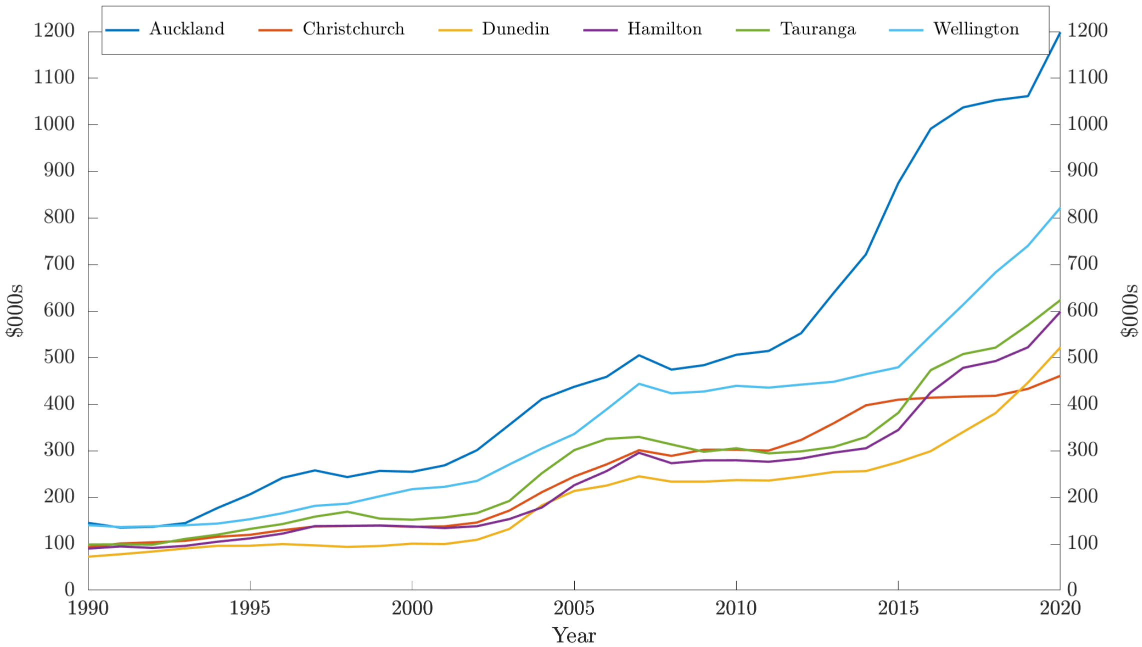
[1] Multi-unit housing structures and cross leases often share land ownership rights among several titles.

[2] Where possible, age is given by the difference between the sales year and the reported year of construction. For properties, where only the decade of construction is available, age is estimated as the difference between the sale year and the mid point of the decade of construction. Any age values that are estimated to be ≤ 0 are set to 1 because age is logged in the regression. Distances are calculated using a 'Haversine' formula which provides the minimum (spherical) distance between two sets of coordinates. These are also logged. There are no zero distances in the dataset.

[3] These boundaries correspond to characteristics of the properties at or above the upper 99.9 percentile for each trait

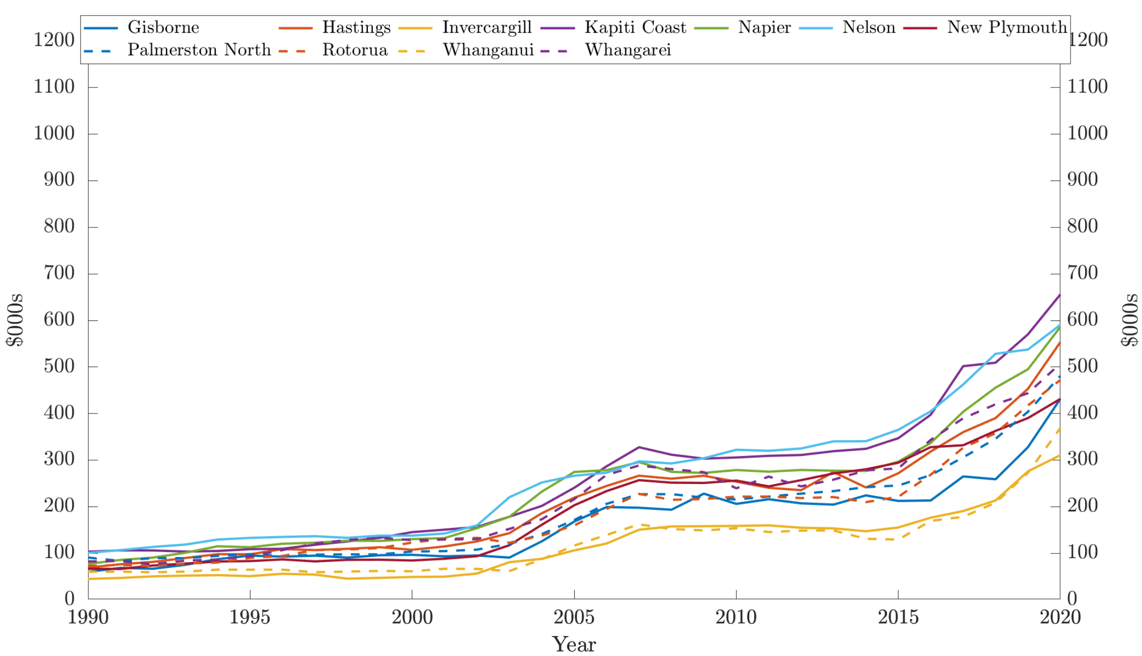
[4] It is assumed that in order to buy and sell a property within a single quarter one or both transactions will likely represent a non arms-length transaction. Hill et al. (2017) note that exclusion of these sales is standard practice in the construction of house price indices.

Figure 1: Median Fixed Attribute House Prices for Metropolitan Areas



Notes: M-FAHPs for the six metropolitan areas. Housing attributes are fixed to median levels across the dwelling stock of all FUAs and can be found in Table 1. The measure tells us the price of a house that has the median amount of attributes in each of the six metro areas across the 1990 to 2020 period. The median attributes are three bedrooms, one bathroom, a floor area of 130m^2, land area of 519m^2, and has a job distance of 6.19km.

Figure 2: Median Fixed Attribute House Prices for Large Regional Centres



centres. The housing stock also tends to be more recently built and has a slightly larger floorspace. Even within the metro areas there is substantial difference between the attributes of houses. As shown in Table 6, houses in Auckland are further away from jobs, on average, compared to the housing stock in metro areas. They also have less land, and are newer, on average, compared to the housing stock, which accords with the rapid development of Auckland over the 1990 to 2020 sample period.

These differences in the attributes of the housing stock between different regions are not reflected in median sales prices. For example, the median house price in Auckland in 2020 was $930,000. The corresponding figure in Tauranga is $727,000. However, the median attribute house in Auckland is likely to be further from job centres and thus entail a longer commute. It is also likely to have less land. A comparison of medians between these two cities is therefore likely to understate price differences on a quality-adjusted basis.

In order to get an idea of the discrepancy between median sales prices and the price of a house with median attributes, we plot the M-FAHPs against the median house prices in six metro areas: Auckland, Tauranga, Hamilton, Wellington, Christchurch and Dunedin. These cities are selected as the time series reveal the benefits of the FAHP. Figure 3 exhibits the results.

Auckland and Wellington have M-FAHPs that exceed their median sales price for the entire sample. This is because the housing stock in these cities has less land and is further from jobs. Meanwhile the median attribute house in Tauranga and Hamilton costs less than the median sales price in these cities. This is due to the fact that houses are larger and newer in Tauranga, while Hamilton houses are on average closer to jobs and have more land.

3.4 Upper and Lower Quartile Attribute Measures of House Prices

The FAHP can be constructed to a representative house at any point in the multivariate distribution of housing attributes. It can also be constructed for sub-samples of specific dwelling types.

In this subsection, we explore these possibilities by plotting the 95th, 75th, 50th (i,e, median), 25th and 5th percentile FAHPs for detached dwellings with exclusive land rights. We consider the same six cities plotted in Figure 3 above.Auckland has substantially more variation in prices compared to other cities.

3.5 Comparison to Repeat Sales index

We also compare the median-FAHP to the sales price appraisal ratio (SPAR), which is more commonly used to measure quality-adjusted variation in house prices over time. The SPAR index augments the repeat sales methods with information on appraised values to better capture changes in quality over time (Bourassa et al. 2006). Because it is an index that is based on repeated observations of individual house prices, it can only measure variation in house prices over time, and is therefore typically normalized to a set value in a given base period. To facilitate comparison, the M-FAHP is normalised to 1 in the first period for each FUA. Figure 5 displays the results for the six FUA regions. Both the SPAR and M-FAHP estimate very similar levels of property price inflation over time for Wellington, Auckland and Christchurch. However the two indices diverge significantly for Dunedin, Tauranga, and, to a lesser degree, Hamilton. In all three cases, the SPAR index exhibits higher levels of inflation than the M-FAHP.

Figure 3: Fixed Attribute House Prices and Median Sales Prices for selected Cities

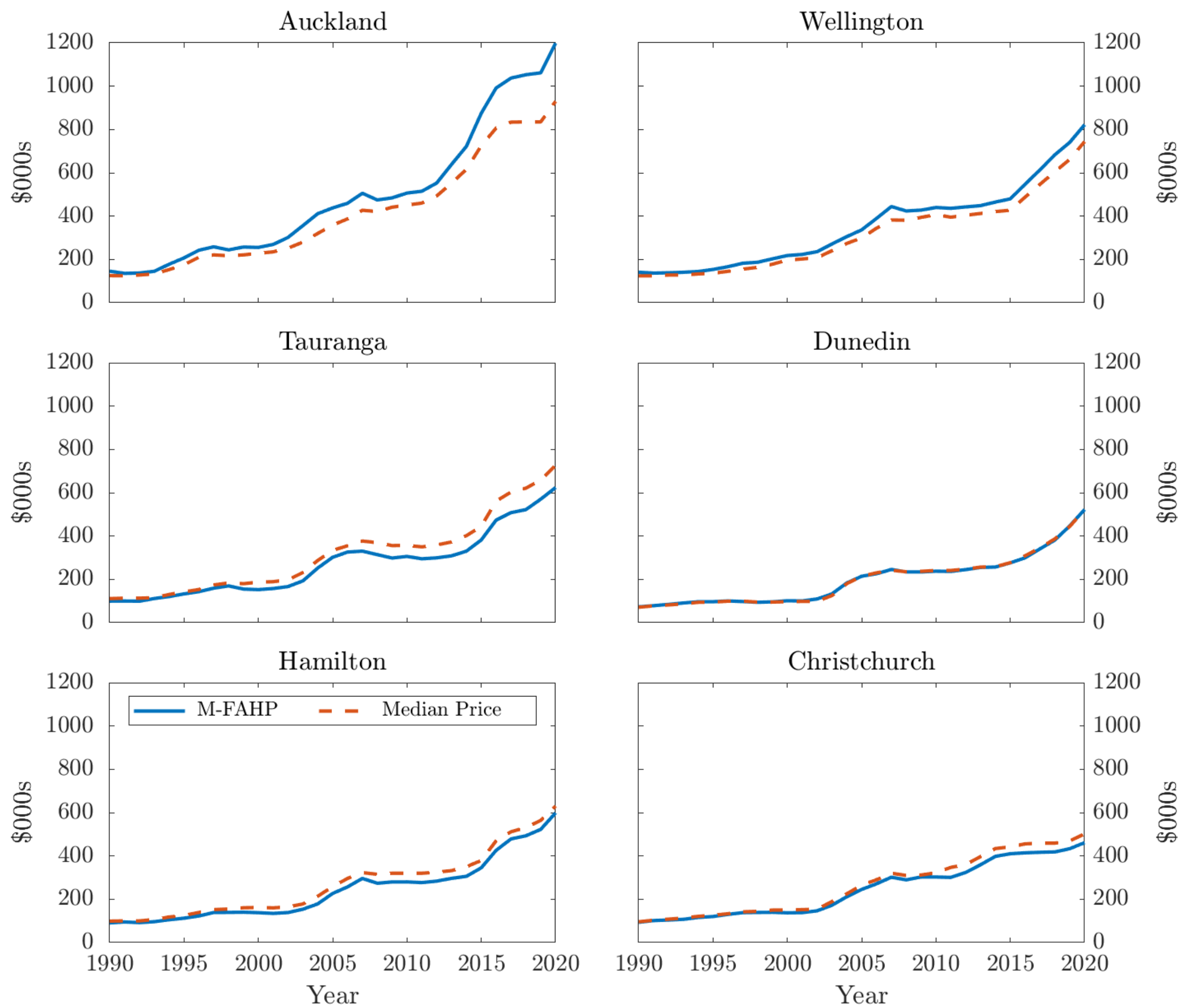
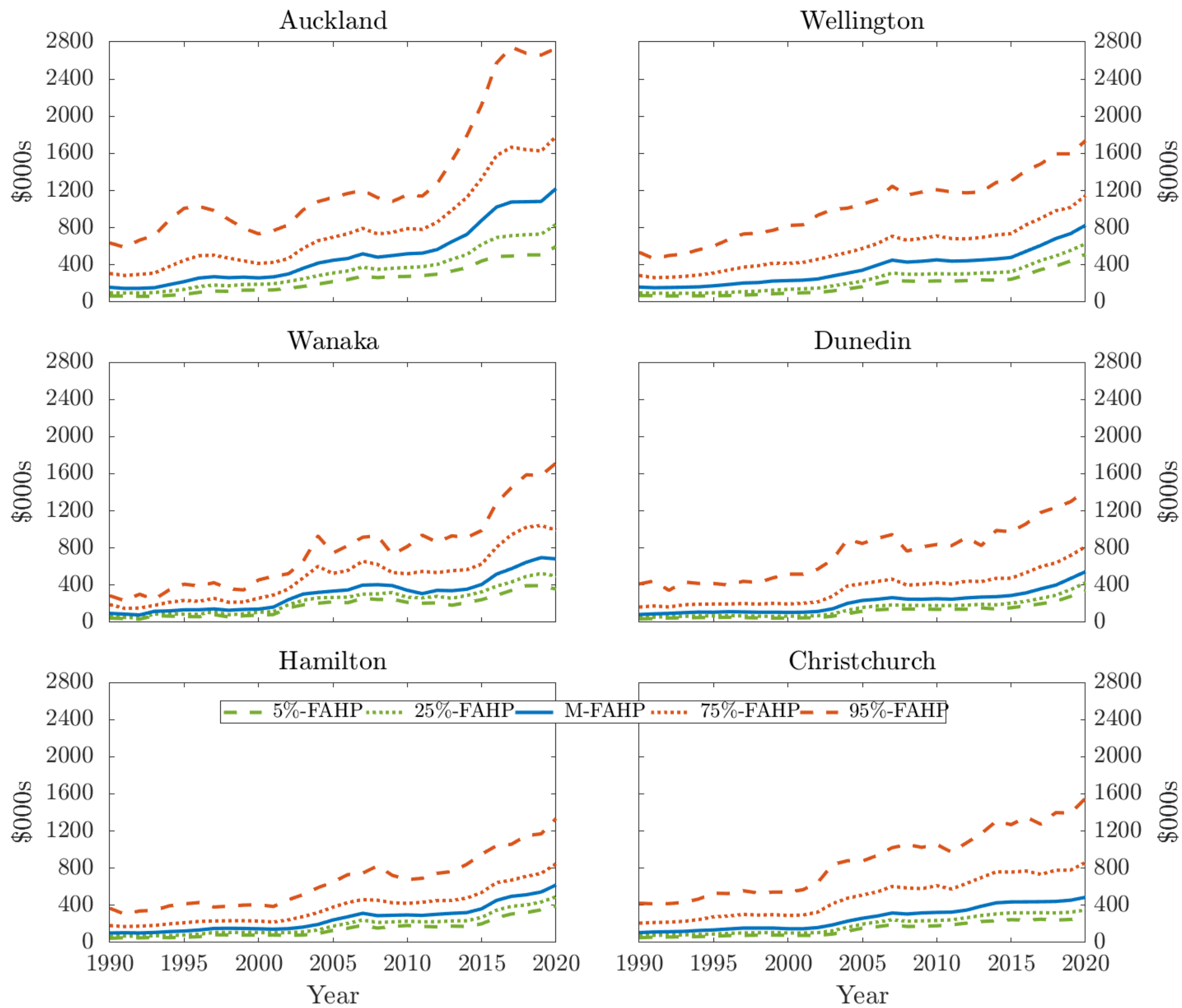
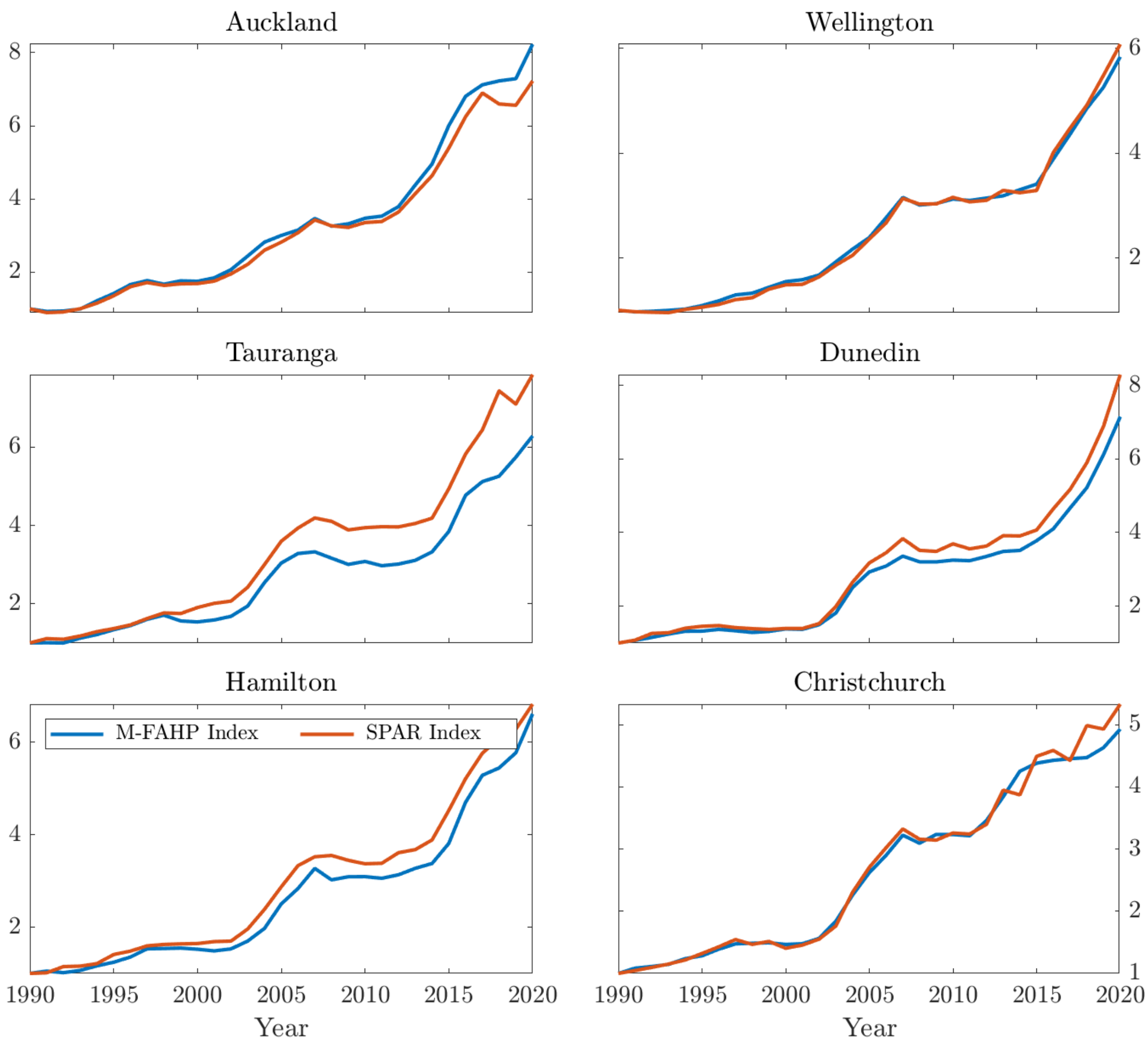


Figure 4: Fixed Attribute House Prices for detached houses with exclusive land title in selected Cities



Notes: M-FAHP is 50th percentile FAHP. The 25%-FAHP is the lower quartile FAHP and the 75%-FAHP is the upper quartile FAHP.

Figure 5: Fixed Attribute House Price Indices and Sales Price Appraisal Ratio for selected Cities



4 Conclusion

This paper proposes a novel approach to the construction of house price measurement that permits comparisons of housing costs across different locations and across different periods of time. The method used hedonic regression to price a house with a fixed bundle of attributes in different urban areas and in different time periods. The resultant measure, fixed attribute house prices (FAHP), thereby allows users to compare house prices across time and space for a house with a fixed level of quality. We implement the method using data on housing across the various urban areas of New Zealand, fixing the attributes to medians across the housing stock of the whole sample. The median FAHP reveals that housing is more expensive in Auckland than implied by median sales prices, and less expensive in Tauranga and Hamilton.

References

[1] Anselin, L. (1988). Spatial econometrics: Methods and Models. Springer.

[2] Anselin, L. (2010). Thirty years of spatial econometrics. Papers in Regional Science 89(1):3–25.

[3] Bailey, M. J., Muth, R. F., and Nourse, H. O. (1963). A Regression Method for Real Estate Price Index Construction. Journal of the American Statistical Association, 58(304):933–942.

[4] Barnard, G. A. (1963). New Methods of Quality Control. Journal of the Royal Statistical Society, 126:255–259.

[5] Beer, M. (2007). Bootstrapping a Hedonic Price Index: Experience from Used Cars Data. Advances in Statistical Analysis, 91(1):77–92.

[6] Bokhari, S. and Geltner, D. (2012). Estimating Real Estate Price Movements for High Frequency Tradable Indexes in a Scarce Data Environment. Journal of Real Estate Finance and Economics, 45:522–543.

[7] Bollerslev, T., Patton, A. J., and Wang, W. (2016). Daily House Price Indices: Construction, Modeling, and Longer-Run Predictions. Journal of Applied Econometrics, 31(6):1005–1025.

[8] Bourassa, S. C., and Hoesli, M. (2017). High-Frequency House Price Indexes with Scarce Data. Journal of Real Estate Literature, 25(1):207–220.

[9] Bourassa, S. C., Hoesli, M., and Sun, J. (2006). A Simple Alternative House Price Index Method. Journal of Housing Economics, 15:80–97.

[10] Case, B., Polakowski, H. O., and Wachter, S. M. (1991). On Choosing Among House Price Index Methodologies. Real Estate Economics, 19(3):286–307.

[11] Case, K., and Shiller, R. (1987). Prices of Single Family Homes Since 1970: New Indexes for Four Cities. New England Economic Review, pages 45–56.

[12] Clapp, J. M., and Giaccotto, C. (1992). Estimating Price Indices for Residential Property: A Comparison of Repeat Sales and Assessed Value Methods. Journal of the American Statistical Association 87(418):300–306.

[13] Clapp, J.M., Salavei Bardos, K., and Wong, S.K. (2012). Empirical estimation of the option premium for residential redevelopment. Regional Science and Urban Economics 42: 240–256.

[14] Conley, T. G. (1999). GMM estimation with cross sectional dependence. Journal of Econometrics, 92:1–45.

[15] Diewert, E., Greenlees, J., and Hulten, C. (2009). Hedonic Imputation versus Time Dummy Hedonic Indexes. In Price Index Concepts and Measurement, pages 161–196. National Bureau of Economic Research.

[16] Elhorst, J. P. (2010). Applied Spatial Econometrics: Raising the Bar. Spatial Economic Analysis, 5(1):9–28.

[17] Eurostat (2013). Handbook on Residential Property Prices Indices (RPPIs). Eurostat methodologies & working papers. Publications Office of the European Union, Luxembourg.

[18] Fleming, D., Grimes, A., Lebreton, L., Mare, D.C., and Nunns, P. (2018). Valuing Sunshine. Regional Science and Urban Economics 68, 268-276.

[19] Goh, Y. M., Costello, G., and Schwann, G. (2012). Accuracy and Robustness of House Price Index Methods. Housing Studies, 27(5):643–666.

[20] Greenaway-McGrevy, R., Pacheco, G., and Sorensen, K. (2021). The Effect of Upzoning on House Prices and Redevelopment Premiums in Auckland, New Zealand. Urban Studies 58(5): 959–976.

[21] Hansen, J. (2006). Australian House Prices: A comparison of hedonic and repeat sales measures. Research Discussion Paper 2006-03, Reserve Bank of Australia.

[22] Helbich, M., Brunauer, W. Vaz, E., and Nijkamp, P. (2014). Spatial Heterogeneity in Hedonic House Price Models: The Case of Austria. Urban Studies, 51(2):390–411.

[23] Hill, R. J. (2013). Hedonic Price Indexes for Residential Housing: A Survey, Evaluation and Taxonomy. Journal of Economic Surveys, 27(5):879–914.

[24] Hill, R. J. and Melser, D. (2008). Hedonic Imputation And The Price Index Problem: An Application To Housing. Economic Inquiry, 46(4):593–609.

[25] Hill, R. C., Melser, D., and Syed, I. (2009). Measuring a Boom and Bust: The Sydney Housing Market 2001-2006. Journal of Housing Economics, 18:193–205.

[26] Hill, R. J., Rambaldi, A. N., and Scholz, M. (2017). Weekly Hedonic House Price Indices: An Imputation Approach from a Spatio-Temporal Model. Proceedings of the 34th General Conference of the Association for Research on Income and Wealth.

[27] Hill, R. J. and Scholz, M. (2017). Can Geospatial Data Improve House Price Indexes? A Hedonic Imputation Approach with Splines. Review of Income and Wealth, 64: 737-756.

[28] Holly, S., Pesaran, M. H., and Yamagata, T. (2010). A spatio-temporal model of house prices in the USA. Journal of Econometrics, 158:160–173.

[29] Jiang, L., Phillips, P., and Yu, J. (2015). New methodology for constructing real estate price indices applied to the Singapore residential market. Journal of Banking and Finance 61(2):121–131.

[30] Kim, M. S. and Sun, Y. (2013). Heteroskedasticity and spatiotemporal dependence robust inference for linear panel models with fixed effects. Journal of Econometrics,177:85–108.

[31] Malpezzi, S. (2008). Hedonic Pricing Models: A Selective and Applied Review. In Housing Economics and Public Policy, pages 67–89.

Table 6: Summary Statistics: Auckland

	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.63	1	0.48	0	0	0	1	1	1
Land Area (m^2)	438.86	448	452.59	0	0	0	696	1,100	1,980
Floor Area (m^2)	145.60	130	69.82	33	56	92	188	278	352
Number of Beds	3.15	3	0.96	1	2	3	4	5	5
Number of Baths	1.52	1	0.78	1	1	1	2	3	4
Approximate Age (Years)	30.51	26	25.46	0	0	9	45	84	103
Deck Indicator (0=No,1=Yes)	0.52	1	0.50	0	0	0	1	1	1
Number of Internal Garages	0.81	1	0.89	0	0	0	2	2	3
Number of Free-standing Garages	0.43	0	0.72	0	0	0	1	2	2
Distance to Jobs (km)	10.61	9.23	7.35	0.72	1.64	5.83	12.37	24.26	37.98
View Indicator (0=No,1=Yes)	0.32	0	0.47	0	0	0	1	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.26	0	0.44	0	0	0	1	1	1

[32] Pace, K. R., Barry, R., and Sirmans, C. F. (1998). Spatial Statistics and Real Estate. Journal of Real Estate Finance and Economics, 17(1):5–13.

[33] Pakes, A. (2003). A Reconsideration of Hedonic Price Indexes with an Application to PC's. American Economic Review, 93(5):1578–1596.

[34] Shiller, R. J. (2008). Derivatives Markets for Home Prices. Working Paper 13962, National Bureau of Economic Research.

[35] Silver, M. (2016). How to better measure hedonic residential property price indexes. Working Paper 16/312, International Monetary Fund.

[36] Silver, M. and Heravi, S. (2007). The Difference between Hedonic Imputation Indices and Time Dummy Hedonic Indices. Journal of Business Economic Statistics, 25(2):239–246.

[37] Sirmans, G. S., Macpherson, D. A., and Zietz, E. N. (2005). The composition of hedonic pricing models. The Journal of Real Estate Literature, 13(1):3–43.

[38] Triplett, J. (2006). Handbook on Hedonic Indexes and Quality Adjustments in Price Indexes. OECD Publishing, Paris.

5 Appendix

5.1 Calculation of average distance to employment centres

For each dwelling, we identify all the SAUs in its FUA that have a centroid within $x_j + 1$ km of the dwelling, where x_j denotes the distance of house j to the centre of the FUA. We refer to this set of SAUs as the 'SAU radius set' for the dwelling. We then take a weighted average of the distance of the dwelling to each of the SAUs in the SAU radius set. Each SAU's weight is the number of jobs in the SAU expressed as a proportion of the total number of jobs in the radius set. We use Census 2018 data for this exercise.

Additional Tables and Figures

Table 7: Summary Statistics: Wellington

	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.75	1	0.43	0	0	0	1	1	1
Land Area (m^2)	506.72	521	441.44	0	0	0	698	1,141	2,112
Floor Area (m^2)	136.73	120	60.65	40	60	94	170	250	320
Number of Beds	3.09	3	0.89	1	2	3	4	5	5
Number of Baths	1.36	1	0.60	1	1	1	2	2	3
Approximate Age (Years)	42.29	40	28.45	0	1	20	61	95	110
Deck Indicator (0=No,1=Yes)	0.53	1	0.50	0	0	0	1	1	1
Number of Internal Garages	0.59	0	0.83	0	0	0	1	2	2
Number of Free-standing Garages	0.56	0	0.77	0	0	0	1	2	3
Distance to Jobs (km)	10.79	9.67	8.73	0.60	1.20	3.95	15.07	25.99	44.19
View Indicator (0=No,1=Yes)	0.44	0	0.50	0	0	0	1	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.22	0	0.41	0	0	0	0	1	1

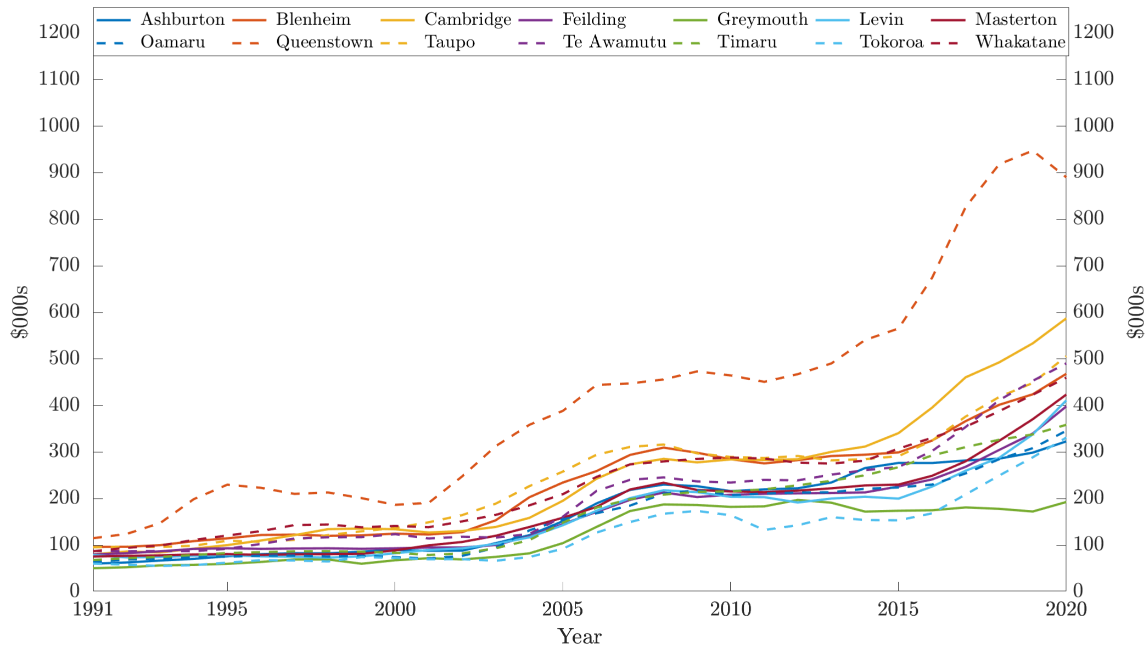
Table 8: Summary Statistics: Hamilton

	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.73	1	0.44	0	0	0	1	1	1
Land Area (m^2)	545.14	639	411.96	0	0	0	760	1,098	1,824
Floor Area (m^2)	145.83	130	60.21	60	74	100	184	260	320
Number of Beds	3.22	3	0.81	2	2	3	4	5	5
Number of Baths	1.34	1	0.58	1	1	1	2	2	3
Approximate Age (Years)	30.48	28	23.54	0	0	11	46	74	96
Deck Indicator (0=No,1=Yes)	0.64	1	0.48	0	0	0	1	1	1
Number of Internal Garages	0.96	1	0.95	0	0	0	2	2	3
Number of Free-standing Garages	0.69	0	0.88	0	0	0	1	2	3
Distance to Jobs (km)	3.79	3.31	2.53	1.00	1.45	2.40	4.36	6.41	15.16
View Indicator (0=No,1=Yes)	0.14	0	0.35	0	0	0	0	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.21	0	0.41	0	0	0	0	1	1

Table 9: Summary Statistics: Tauranga

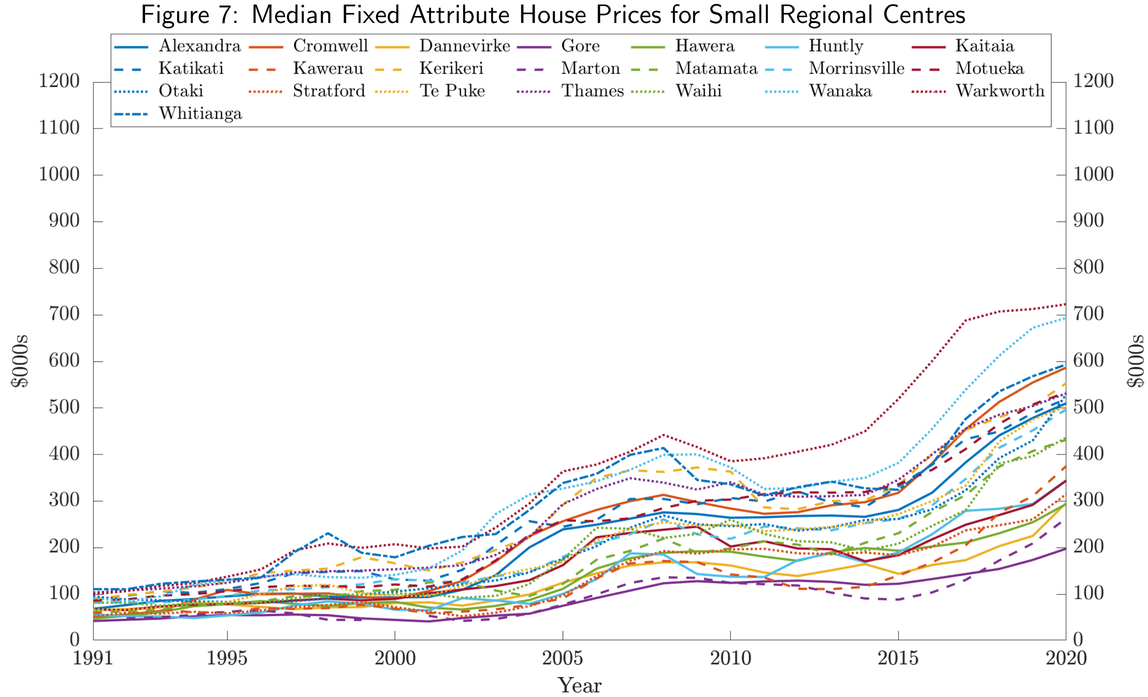
	Mean	Median	Std.Dev.	p01	p05	p25	p75	p95	p99
Land Indicator (0=No,1=Yes)	0.70	1	0.46	0	0	0	1	1	1
Land Area (m^2)	461.48	500	389.41	0	0	0	700	1,011	1,550
Floor Area (m^2)	155.36	150	60.04	55	80	110	190	260	333
Number of Beds	3.14	3	0.76	1	2	3	4	4	5
Number of Baths	1.42	1	0.58	1	1	1	2	2	3
Approximate Age (Years)	22.97	20	17.44	0	1	9	35	56	68
Deck Indicator (0=No,1=Yes)	0.53	1	0.50	0	0	0	1	1	1
Number of Internal Garages	0.93	1	0.95	0	0	0	2	2	3
Number of Free-standing Garages	0.49	0	0.81	0	0	0	1	2	2
Distance to Jobs (km)	4.96	4.05	2.90	1.05	1.90	3.07	5.79	11.58	13.76
View Indicator (0=No,1=Yes)	0.29	0	0.45	0	0	0	1	1	1
Multi-Unit Indicator (0=No,1=Yes)	0.14	0	0.35	0	0	0	0	1	1

Figure 6: Median Fixed Attribute House Prices for Medium Regional Centres



Note: Hedonic regressions are run over a two-year period to smooth the resultant price measure. The figure for 1991 is based on sales in 1990 and 1991.

Figure 7: Median Fixed Attribute House Prices for Small Regional Centres



Note: Hedonic regressions are run over a two-year period to smooth the resultant price measure. The figure for 1991 is based on sales in 1990 and 1991.