A Model of HDB Resale Prices

Key Features & Insights

Presentation Outline

1. Overview & Objectives

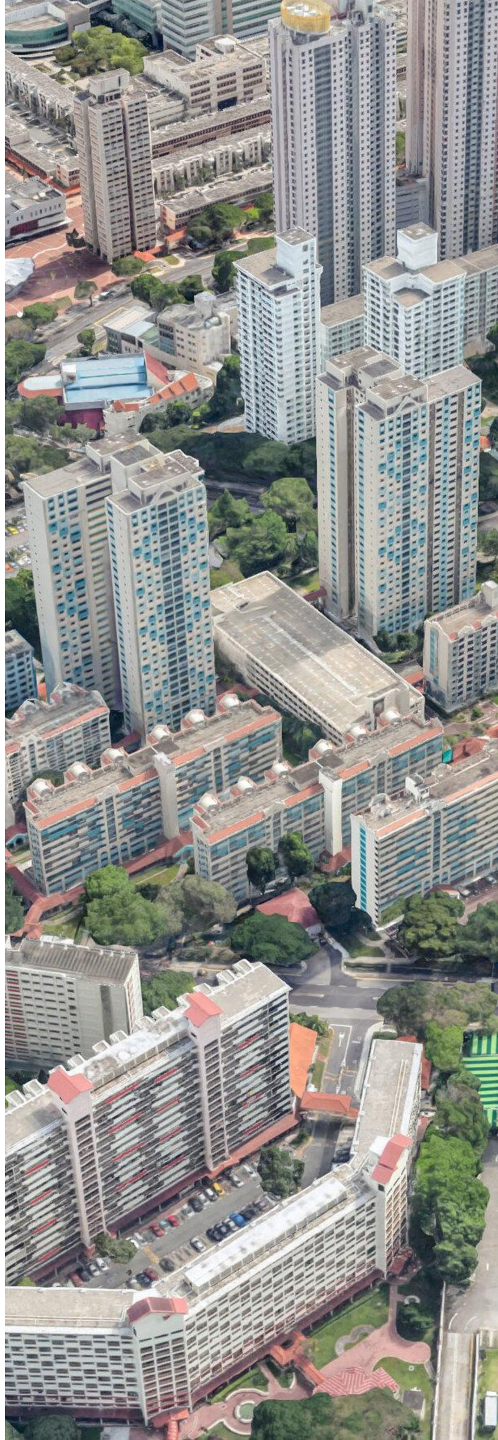
Context :: The Value of Modelling HDB Resale Prices

- An overwhelming majority (78%) of resident households in Singapore live in HDB apartments (i.e., public housing) [1]

- There is thus keen interest in identifying features strongly associated with HDB resale prices, as well as being able to predict prices, amongst:

  (a) **Home owners / buyers:**
  to assess what an apartment's fair value might be
  to identify apartments that fit their budget/needs

  (b) **Policy makers**
  to identify features residents value, to aid with town planning



1. Overview & Objectives

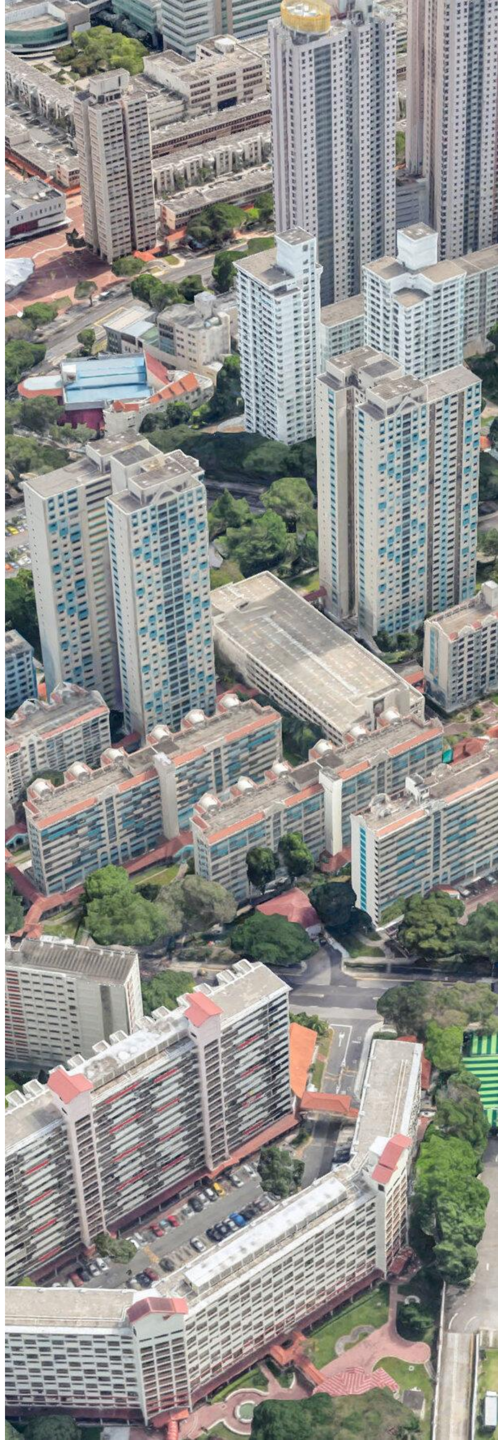
HDB Resale Price Modelling Objectives

(a) Inference

To separably identify features strongly associated with resale prices, by assessing their *statistical* and *practical* significance

(b) Prediction

To predict resale prices with well, with *as narrow a deviation from transacted prices as possible*



2. Data

HDB Resale Price Dataset

- Resale price data over a significant time span, with a large no. of observations [2]
  - ~ 9 years (2012 – ‘21)
  - ~ 150,000 recorded transactions

- Incorporating data on a wide range of features (>70), covering the following broad feature categories:
  - <u>Apartment’s</u>
    - Physical characteristics (e.g., floor area, floor level)
    - Remaining lease period
    - Housing block characteristics (e.g., flat type composition)
  - <u>Surrounding</u>
    - Transport infrastructure (e.g., MRT stations)
    - Amenities (e.g., malls, hawker centres)
    - Schools

3. Empirical Approach

(-) Dataset Train-Test Splitting

- Dataset split 80:20 into ‘training’ and ‘testing’ datasets (*)

(*) The source data package includes ‘training’ and ‘testing’ datasets for which resale price data is only available in the former.
We thus utilise the ‘training’ dataset for analysis, and perform ‘train-test’ splitting on this dataset.

(a) Inference :: To Separably Identify Features Strongly Associated with Resale Prices

- Unregularised Multivariate OLS regression modelling using ‘training’ data (*)

(*) Appendix A: Utilising Unregularised (Instead of Regularised) Regression Modelling for Inference

- *Hypothesis-focused approach* to feature selection and engineering, as interpretation of regression coefficients is of primary interest for this analysis
- Contextual knowledge (e.g., news reports, interview with a practicing property agent), and exploratory data analysis utilised to derive features
- Feature set examined for multicollinearity as it causes unstable coefficient estimates, and understatement of statistical significance:
    - Feature set’s Variance Inflation Factors (VIFs) examined
    - VIFs <10 : indicating absence of multicollinearity [3]

3. Empirical Approach

Multivariate OLS Regression Model :: Feature Sets

$$Resale\ Price_{i,t} = \beta_0 + \beta_1\boldsymbol{X}_{i,t} + \beta_2\boldsymbol{\gamma}_{i,t} + \beta_3\boldsymbol{\varphi}_{i,t} + \beta_4\boldsymbol{\theta}_{i,t} + \beta_5\boldsymbol{\omega}_{i,t} + \beta_6\boldsymbol{Town}_i + \beta_7\,\boldsymbol{Year}_t + \varepsilon_{i,t}$$

- $\boldsymbol{X}$: Apartment Characteristics
- $\boldsymbol{\gamma}$: Access to Public Transport Infrastructure
- $\boldsymbol{\varphi}$: Access to Amenities
- $\boldsymbol{\theta}$: Travel Cost to the CBD via the MRT Network
- $\boldsymbol{\omega}$: Proximity to ‘Branded’ Schools
- $\boldsymbol{Town}, \boldsymbol{Year}$: Fixed Effects

(b) Prediction :: With as Narrow a Deviation from Transacted Prices as Possible

- Apply regularisation (ridge, lasso) on previously unregularised multivariate model
- Compare prediction metrics with/without regularisation via k-folds cross validation on ‘training’ data, select an approach that best predicts prices
- Report prediction metric results on ‘testing’ data

3. Empirical Approach

Multivariate OLS Regression Model

$$Resale\ Price_{i,t} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{\gamma}_{i,t} + \beta_3 \boldsymbol{\varphi}_{i,t} + \beta_4 \boldsymbol{\theta}_{i,t} + \beta_5 \boldsymbol{\omega}_{i,t} + \beta_6 \boldsymbol{Town}_i + \beta_7 \boldsymbol{Year}_t + \varepsilon_{i,t}$$

$\boldsymbol{X}$: Apartment Characteristics	Remarks
Floor Area (Sqm) , Floor Area (Sqm) ^{2}	-
Floor Level , Floor Level ^{2}	-
Flat Type: If DBSS	To reflect these flat types' private property-like features
Flat Type: If Terrace	*Reference category*: *flat type is neither of these types*
Flat Type: If Maisonette / Loft	
Flat Type: If Duxton (S1/S2)	
Remaining Lease Years , Remaining Lease Years ^{2}	-
Within Block: If Rental Units Present	To capture possible neighbour preference

3. Empirical Approach

Multivariate OLS Regression Model

$$Resale\ Price_{i,t} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{\gamma}_{i,t} + \beta_3 \boldsymbol{\varphi}_{i,t} + \beta_4 \boldsymbol{\theta}_{i,t} + \beta_5 \boldsymbol{\omega}_{i,t} + \beta_6 \boldsymbol{Town}_i + \beta_7\, \boldsymbol{Year}_t + \varepsilon_{i,t}$$

$\boldsymbol{\gamma}$ **: Access to Public Transport Infrastructure**	**Remarks**
Nearest MRT Station (If: Within 500m)	-
Nearest MRT Station (If: >500 to 1000m)	
Nearest MRT Station: Is a Bus & MRT Interchange	*Reference category*:
Nearest MRT Station: Is a MRT Interchange (Only)	*Nearest MRT station: neither a bus nor MRT interchange*
Nearest MRT Station: Is a Bus Interchange (Only)	
Nearest Bus Stop (If: Within 150m)	-

3. Empirical Approach

Multivariate OLS Regression Model

$$Resale\ Price_{i,t} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{\gamma}_{i,t} + \beta_3 \boldsymbol{\varphi}_{i,t} + \beta_4 \boldsymbol{\theta}_{i,t} + \beta_5 \boldsymbol{\omega}_{i,t} + \beta_6 \boldsymbol{Town}_i + \beta_7\, \boldsymbol{Year}_t + \varepsilon_{i,t}$$

$\boldsymbol{\varphi}$: Access to Amenities	Remarks
Nearest Mall (If: Within 500m)	-
Nearest Mall (If: >500 to 1000m)	
Nearest Hawker Centre (If: Within 500m)	-
Nearest Hawker Centre (If: >500 to 1000m)	
Nearest Hawker Centre (If: Large)	Large: >100* Food & Market Stalls * median no. of stalls (amongst all resale price observations)

3. Empirical Approach

Multivariate OLS Regression Model

$$Resale\ Price_{i,t} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{\gamma}_{i,t} + \beta_3 \boldsymbol{\varphi}_{i,t} + \beta_4 \boldsymbol{\theta}_{i,t} + \beta_5 \boldsymbol{\omega}_{i,t} + \beta_6 \boldsymbol{Town}_i + \beta_7 \boldsymbol{Year}_t + \varepsilon_{i,t}$$

$\boldsymbol{\theta}$: Travel Cost to the CBD via the MRT Network

Travel Cost , Travel Cost ^{2}

Remarks / Hypotheses

- HDB residents tend to travel by the MRT, and there is a penalty (premium) to being further (closer) to the Central Business District (CBD) in terms of travel cost along the MRT network
- Penalty may be due to the added inconvenience of accessing job opportunities in the CBD, and lower potential rental income yield for home owners
- Expect the penalty to diminish at tail ends of the network due to presence of regional economic centres (e.g., Jurong Industrial Zone, Loyang Aviation Cluster / Changi Business Park) [4]

3. Empirical Approach

Multivariate OLS Regression Model

$$Resale\ Price_{i,t} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{\gamma}_{i,t} + \beta_3 \boldsymbol{\varphi}_{i,t} + \beta_4 \boldsymbol{\theta}_{i,t} + \beta_5 \boldsymbol{\omega}_{i,t} + \beta_6 \boldsymbol{Town}_i + \beta_7 \boldsymbol{Year}_t + \varepsilon_{i,t}$$

$\boldsymbol{\theta}$: Travel Cost to the CBD via the MRT Network

Travel Cost , Travel Cost ^{2}

Remarks / Feature Construction Approach

- Resale price data spans 2012 – '21, and the network has evolved during the period (e.g., introduction of the Downtown Line (2017), Thompson-East Cost Line (2020)) [5,6]
- Expect home buyers to consider evolution of the MRT network when making purchase decisions (alongside other future-oriented area development plans), and thus consider the MRT network as at 2024
- Travel Cost = Minimum No. of MRT Stations to a list of CBD Stations *
  (*transfers across MRT lines modelled as travelling through another MRT station – to reflect cost of making transfers)

3. Empirical Approach

Multivariate OLS Regression Model

$$Resale\ Price_{i,t} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{\gamma}_{i,t} + \beta_3 \boldsymbol{\varphi}_{i,t} + \beta_4 \boldsymbol{\theta}_{i,t} + \beta_5 \boldsymbol{\omega}_{i,t} + \beta_6 \boldsymbol{Town}_i + \beta_7 \boldsymbol{Year}_t + \varepsilon_{i,t}$$

$\boldsymbol{\omega}$: Proximity to 'Branded' Schools	
No. of 'Branded' Primary Schools (Within 1 km)	No. of 'Branded' Secondary Schools (Within 1 km)
No. of 'Branded' Primary Schools (>1 to 2 km)	No. of 'Branded' Secondary Schools (>1 to 2 km)

Remarks / Hypotheses

- Priority for admission into a given *primary school* is based on proximity, with children living (a) within 1km of the school being granted higher priority than those living (b) between 1km - 2km, and (c) beyond 2km [7]
- Given competition for places in 'branded' *primary schools*, parents may be willing to pay a premium to purchase homes near these schools, to increase chances of their children being granted admission [8]
- Although proximity-based priority admission to *secondary schools* *is not practiced* – it is possible but less certain if being located close by these schools carries a resale price premium

3. Empirical Approach

Multivariate OLS Regression Model

$$Resale\ Price_{i,t} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{\gamma}_{i,t} + \beta_3 \boldsymbol{\varphi}_{i,t} + \beta_4 \boldsymbol{\theta}_{i,t} + \beta_5 \boldsymbol{\omega}_{i,t} + \beta_6 \boldsymbol{Town}_i + \beta_7 \boldsymbol{Year}_t + \varepsilon_{i,t}$$

$\boldsymbol{\omega}$: Proximity to 'Branded' Schools

No. of 'Branded' <u>Primary</u> Schools (Within 1 km)	No. of 'Branded' <u>Secondary</u> Schools (Within 1 km)
No. of 'Branded' <u>Primary</u> Schools (>1 to 2 km)	No. of 'Branded' <u>Secondary</u> Schools (>1 to 2 km)

Remarks / Feature Construction Approach

- Rely on a school classification approach used in a research paper by the Singapore Children's Society to identify 'branded' primary and secondary schools
- 'Branded' primary schools: offer the Gifted Education Programme, are affiliated to Integrated Programme Secondary Schools, or are government-aided
- 'Branded' secondary schools: offer the Integrated Programme, or are autonomous schools [9]

3. Empirical Approach

Multivariate OLS Regression Model

$$Resale\ Price_{i,t} = \beta_0 + \beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{\gamma}_{i,t} + \beta_3 \boldsymbol{\varphi}_{i,t} + \beta_4 \boldsymbol{\theta}_{i,t} + \beta_5 \boldsymbol{\omega}_{i,t} + \beta_6 \boldsymbol{Town}_i + \beta_7 \boldsymbol{Year}_t + \varepsilon_{i,t}$$

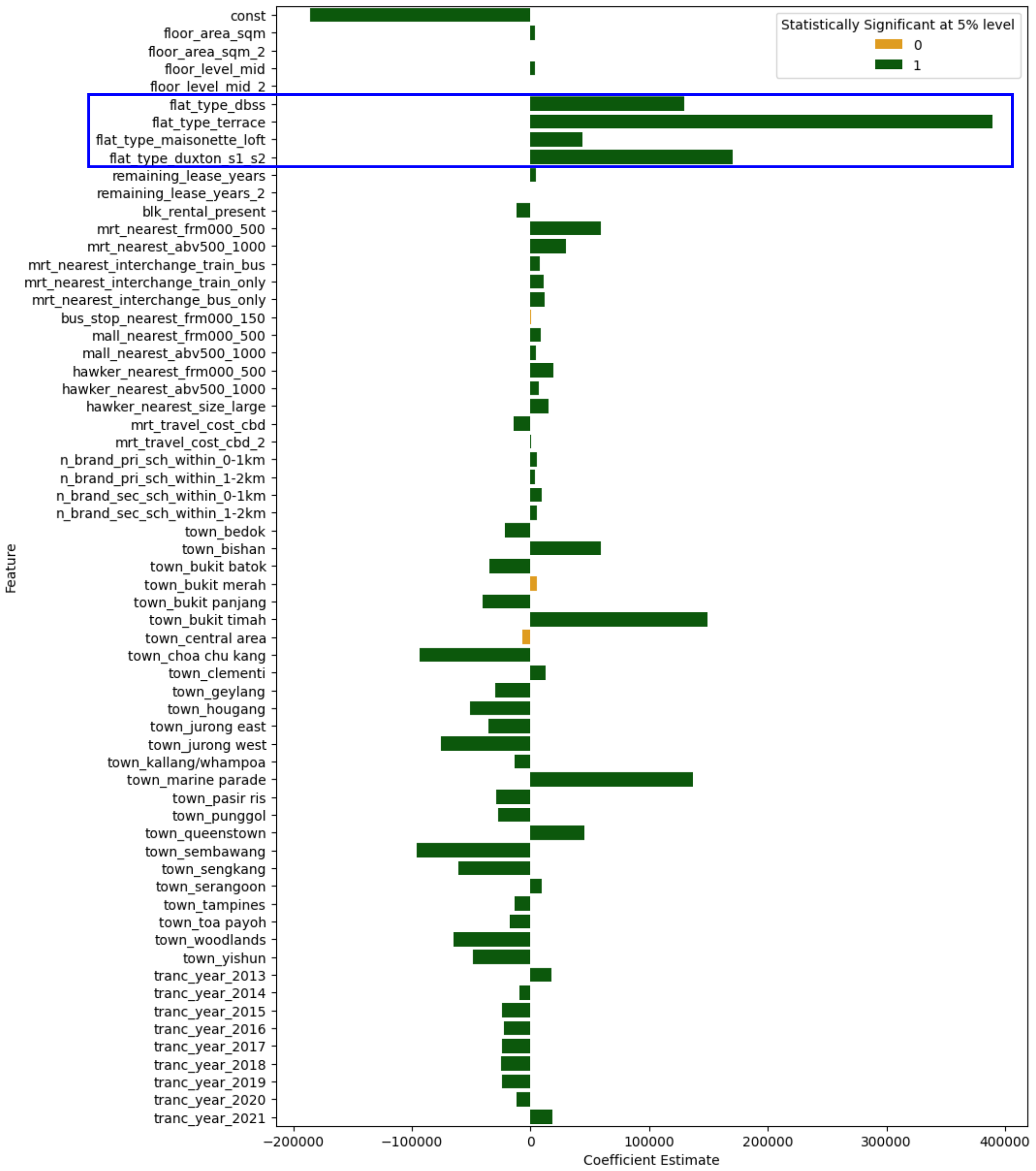
$\boldsymbol{Town}$: Town Fixed Effects

- To capture time-invariant, unobserved (i.e., unmeasured) town characteristics (e.g., natural amenities (proximity to nature reserves), intangible character (e.g., Katong's Peranakan heritage))
- Modelled as a set of 'Town' dummies – with 'Ang Mo Kio' as the reference town

$\boldsymbol{Year}$: Year Fixed Effects

- To capture year-specific effects/shocks (e.g., property price inflation, covid-19 induced supply disruptions)
- Modelled as a set of 'Year' dummies – with 2012 as the reference year

4. Results: Inference



Features Most Strongly Associated with Resale Price

Apartment Characteristics

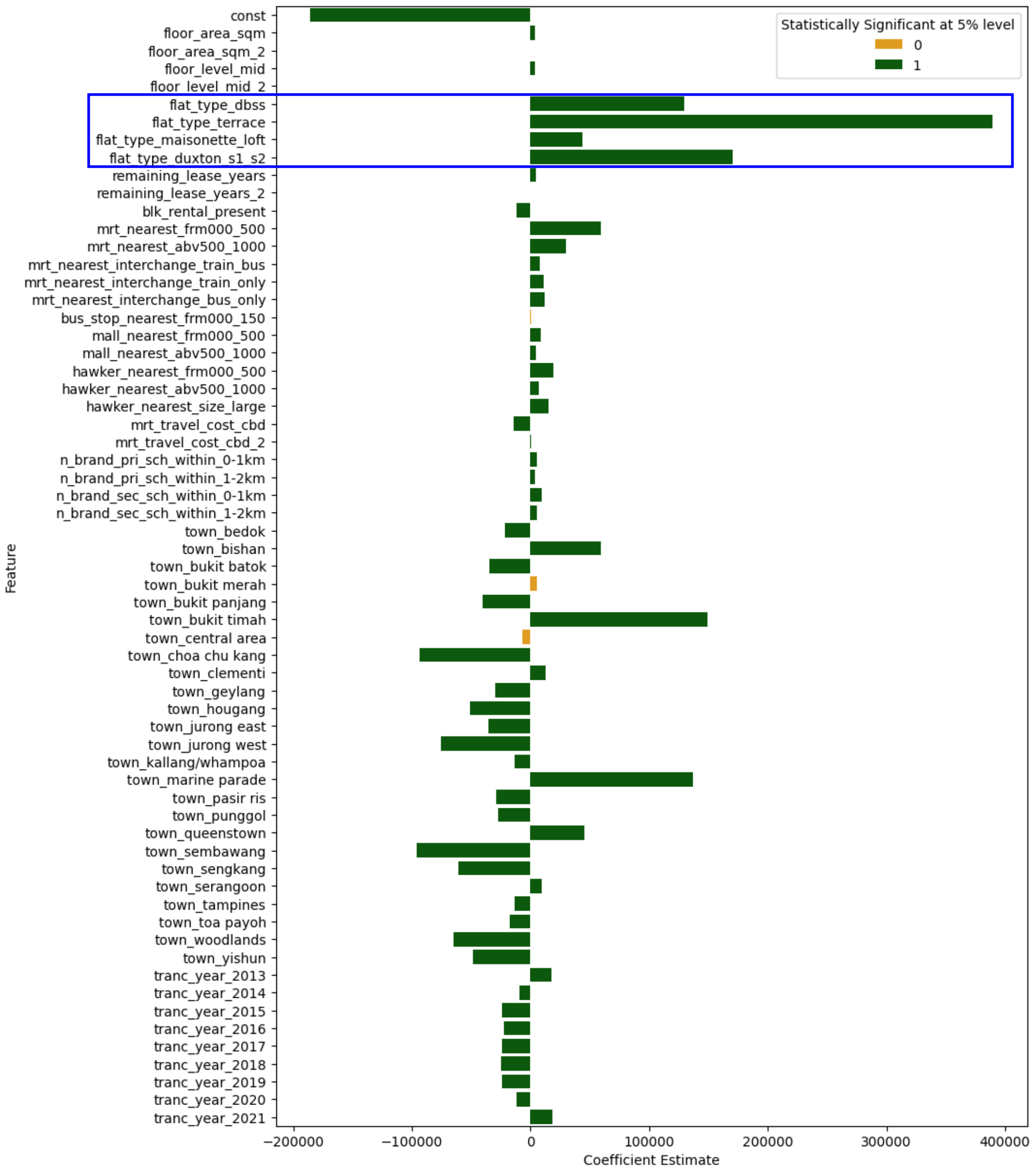
(1) Exceptional Flat Types

- Terrace (+ ~$390,000)
- Duxton S1/S2 (+ ~$170,000)
- DBSS (+ ~$130,000)
- Maisonette/Loft (+ ~$44,000)

Flat types embodying observable private property-like features have the highest coefficient estimates

(L) HDB Terrace units akin to a landed-property
(M-L) Duxton S1/S2 units, iconic public housing development with sky terraces
(M-R) DBSS units by private developers, akin to condominiums externally and with premium interiors [10]
(R) Maisonette /Loft units with high-ceilings, akin to a 'double-story landed property in the sky'

4. Results: Inference



Features Most Strongly Associated with Resale Price

Apartment Characteristics

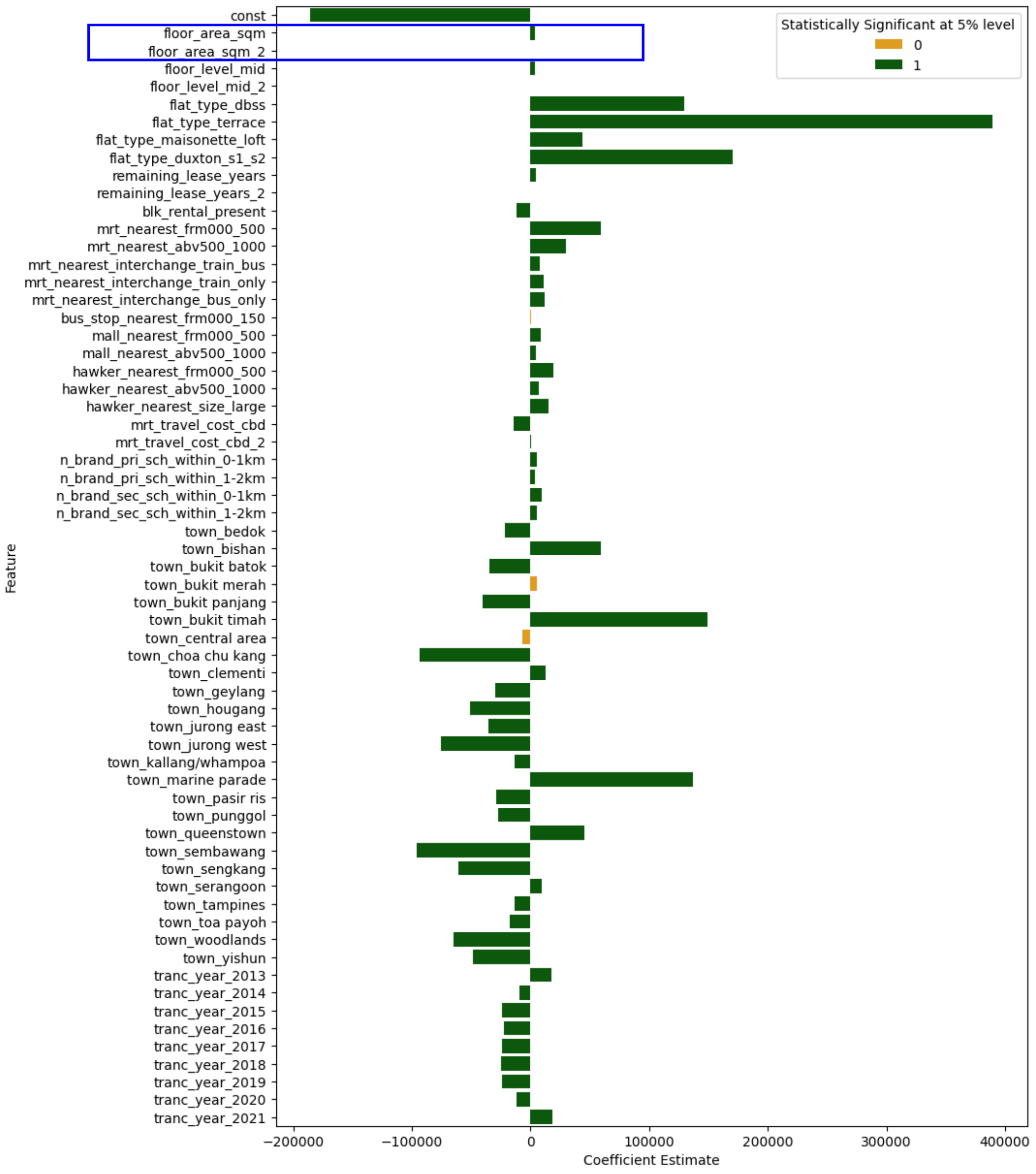
(1) Exceptional Flat Types

- Terrace (+ ~$390,000)
- Duxton S1/S2 (+ ~$170,000)
- DBSS (+ ~$130,000)
- Maisonette/Loft (+ ~$44,000)

On average and holding other features constant (e.g., floor area), home buyers are estimated to value apartments of these flat types over others (e.g., ‘*new generation*’, ‘*improved*’, *that do not possess observable private property-like features*) at the amounts above

However, these estimates may also embody the effects of unobserved features associated with these flat types (e.g., *more luxurious home renovation works, if home owners of these flat types tend to invest more on renovating their homes*)

4. Results: Inference



Features Most Strongly Associated with Resale Price

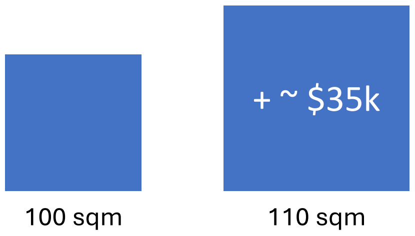
Apartment Characteristics

(2) Flat's Floor Area

- Floor Area (sqm) (+ ~$3,500/sqm)

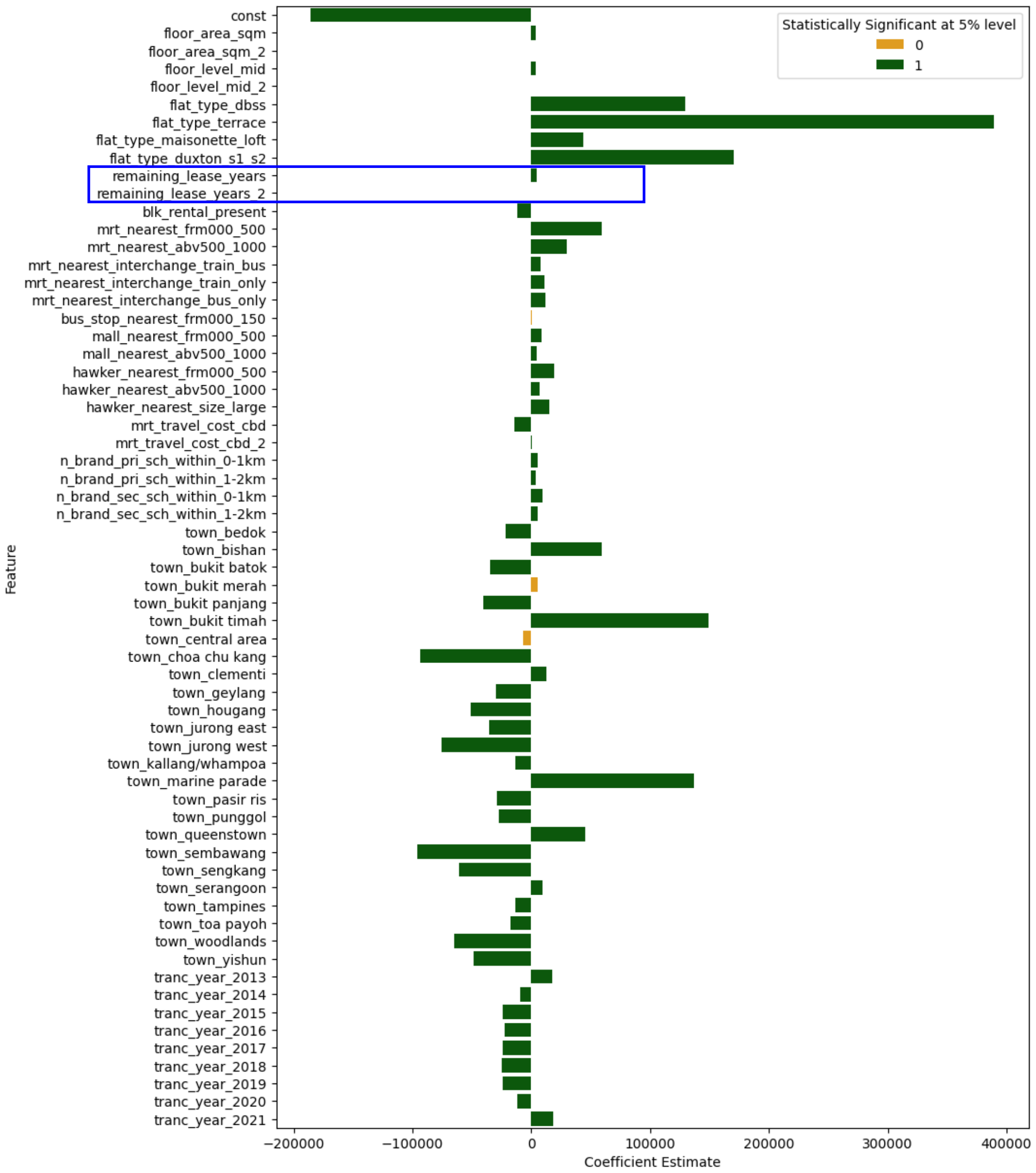
Larger flats command a price premium of ~ $3,500/sqm (*)
(on average, holding other features constant)

Considering that the average size of a flat in our sample is ~100 sqm: 10% (10 sqm) increase in floor area (from the mean) is thus associated with a $35,000 increase in resale price



(*) The 'floor area – resale' price relationship is almost linear, as the coefficient on 'Floor Area (Sqm)^2' is practically negligible (at value = 3)

4. Results: Inference



Features Most Strongly Associated with Resale Price

Apartment Characteristics

(3) Flat's Remaining Lease Years

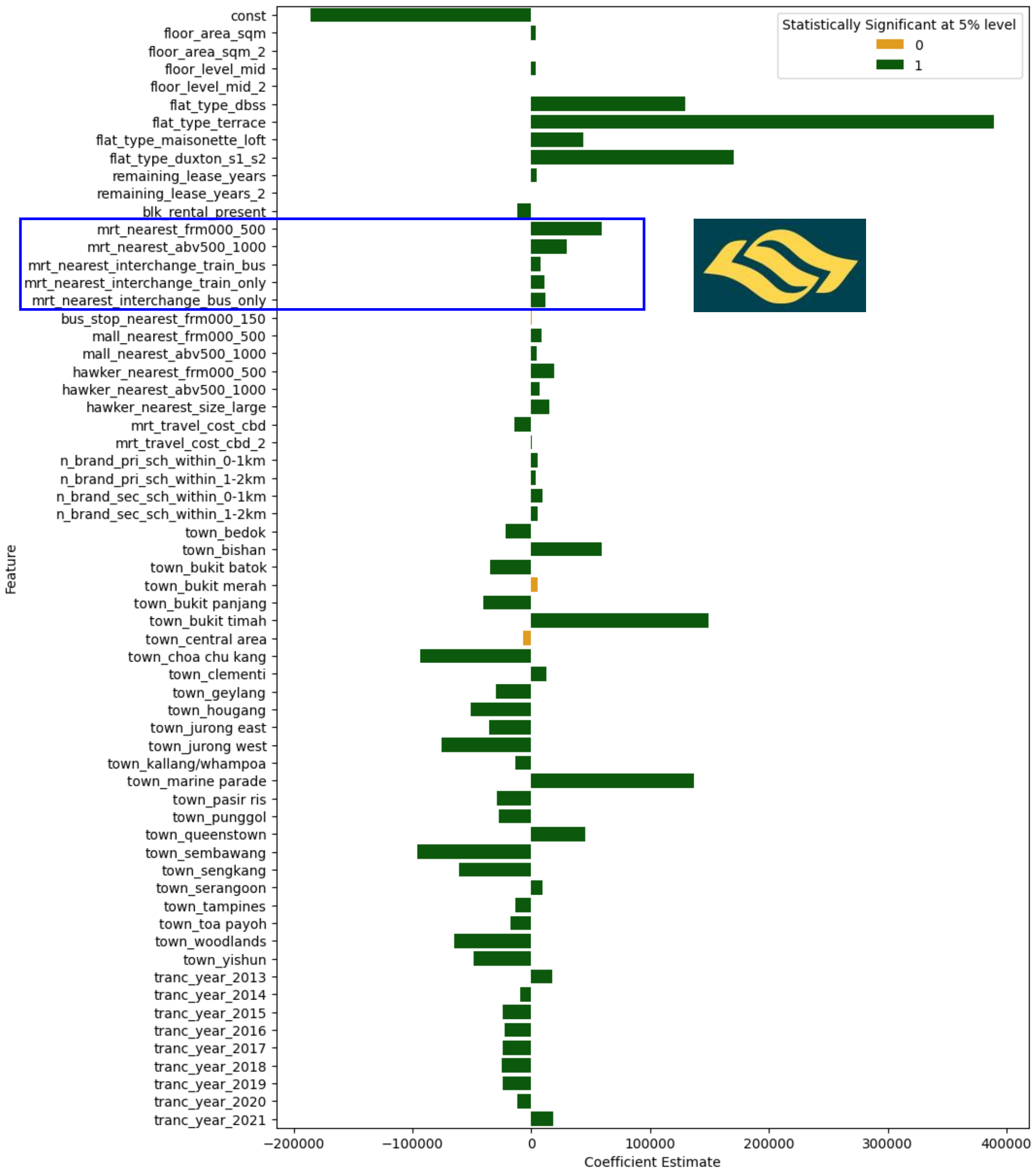
- Remaining Lease Years (+ ~$4,300/year)

Considering the matter of lease decay, an additional remaining lease year is associated with a $4,300 increase in resale price (*)
(on average, and holding other features constant)

A 10 year increase in remaining lease is thus associated with a $43,000 increase in resale price

(*) 'Remaining Lease Years – Resale Price' relationship: we do not find support for a non-linear relationship between remaining lease years and resale price - but this may be an artifact of our sample not having observations that are closer to lease termination (average remaining lease = 75, min = 45 years) – where we might expect rapidly diminishing resale prices closer to termination

4. Results: Inference



Features Most Strongly Associated with Resale Price

Public Transport Connectivity

(1) Proximity to an MRT Station

- Nearest MRT Station (If: Within 500m) (+ ~$59,000)
- Nearest MRT Station (If: >500 to 1000m) (+ ~$30,000)

Being closer to an MRT station commands a price premium:

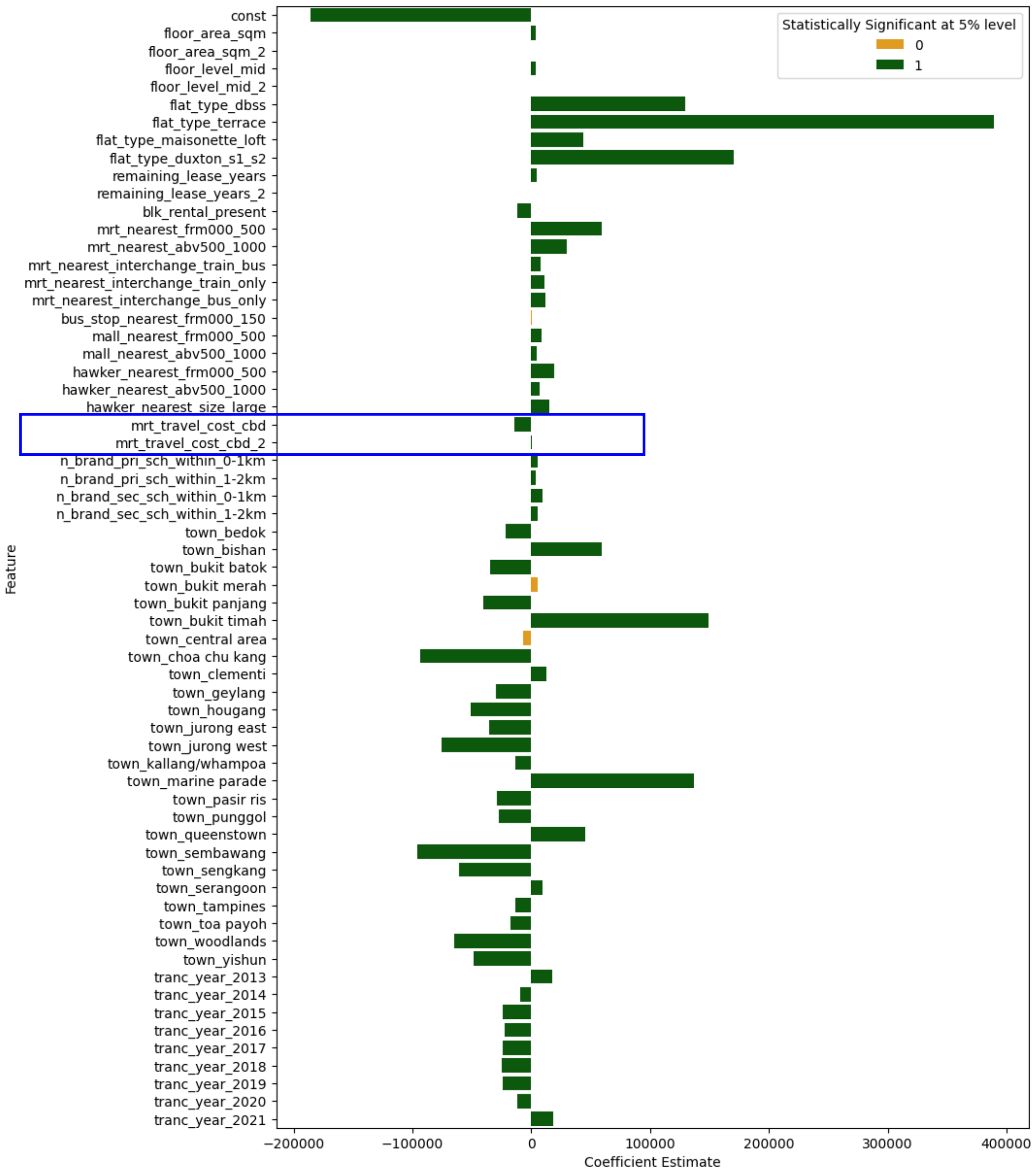
Flats within 0.5km (0.5 to 1km) to the nearest MRT station are on average $59,000 ($30,000) more expensive than flats located 1km away, holding other features constant

(2) Nearest MRT Station Being a Public Transport Hub

Price premiums are also associated with the nearest MRT station being a public transport interchange:

Resale prices being $8,000 to $12,000 higher when the nearest MRT station is a bus and/or MRT interchange, compared to it being a MRT station alone

4. Results: Inference



Features Most Strongly Associated with Resale Price

Travel Cost to the CBD via the MRT Network

- Travel Cost (- ~$14,000 / cost unit)

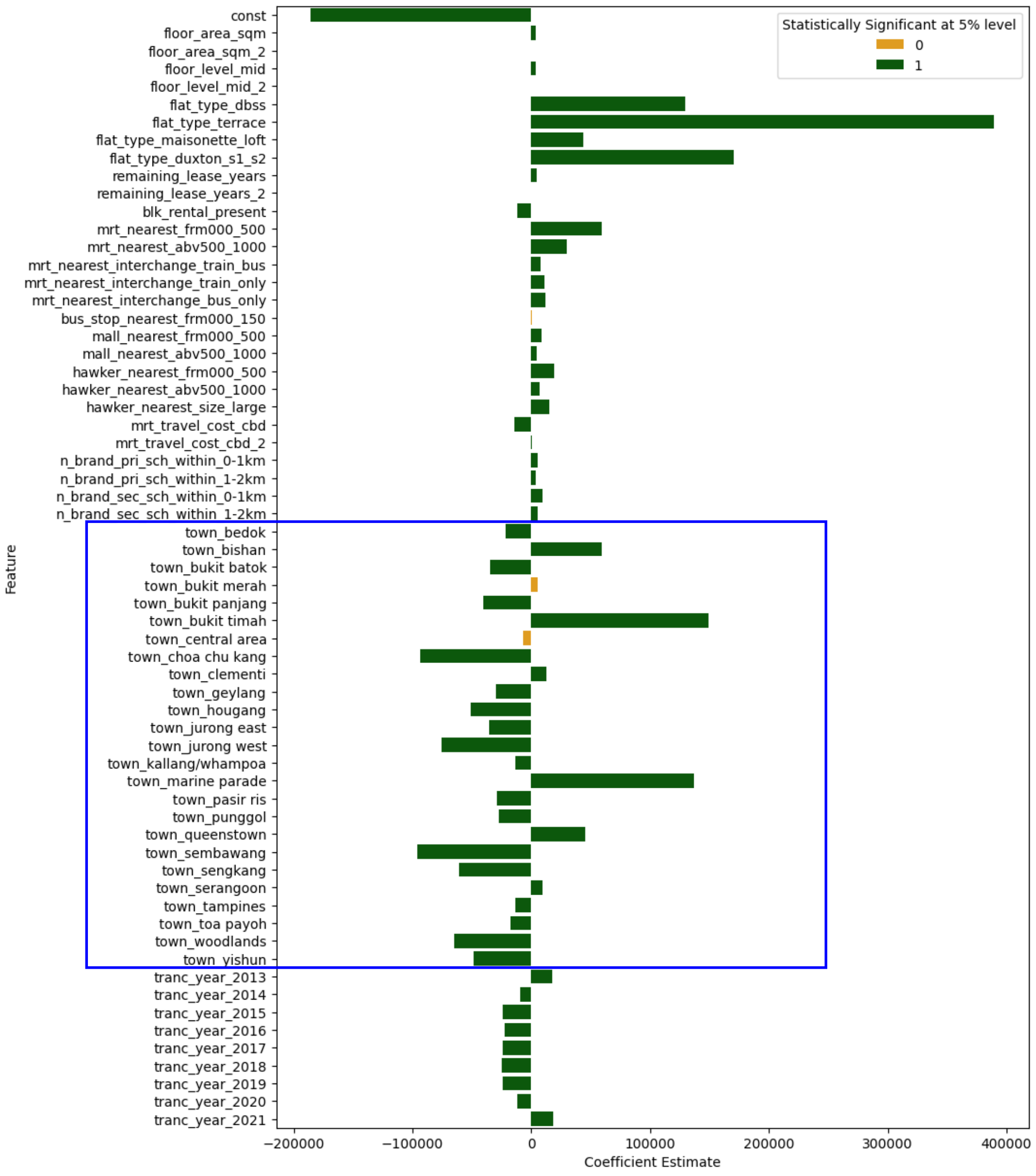
A one unit increase in travel cost to the CBD via the MRT network *is akin to travelling an additional MRT stop to reach the CBD.*

Considering that the average travel cost in our sample is 10, this implies a penalty of ~$140,000 when the travel cost is at such – on average, and holding other features constant

(*) While there is evidence of the travel cost penalty diminishing at regions further away from the CBD (perhaps due to closer proximity to regional economic clusters) - the rate at which the penalty diminishes is low, as the coefficient estimate on the travel cost-squared term is ~$160

4. Results: Inference



Features Most Strongly Associated with Resale Price

Town-level Fixed Effects

Relative to prices of resale flats sold in Ang Mo Kio (the reference town), and after controlling for observable features in our model, resale flats sold in the following towns were priced substantially higher/lower:

- Bukit Timah (+ ~$149,000)
- Marine Parade (+ ~$137,000)
- Bishan (+ ~$59,000)
- Sembawang (- ~$96,000)
- Chua Chu Kang (- ~$93,000)
- Jurong West (- ~$76,000)

These differences are practically substantial - considering that the mean resale price in our data is ~$450,000

5. Results: Prediction

Recap: Background & Approach

As the objective of this analysis is to build a model that predicts resale prices well, ridge and lasso regularisation has been applied on the previously unregularised multivariate model – to assess if regularisation improves its predictive ability and generalisability

Prediction Metrics

		Unregularised	Ridge	Lasso
Training	R-squared	0.89	0.89	0.89
	MAE	$36,650	$36,650	$36,650
	MAPE	0.086	0.086	0.086
k-Folds Cross-Val	R-squared	0.89	0.89	0.89
	MAE	$36,680	$36,680	$36,680
	MAPE	0.086	0.086	0.086
Testing	R-squared	0.89	0.89	0.89
	MAE	$36,360	$36,360	$36,360
	MAPE	0.086	0.086	0.086

- No discernible difference in predictive performance across 'unregularised', 'ridge' and 'lasso' approaches (*)

  (*) Expected, as search for optimal regularisation alphas reveals that optimal values are close to zero (ridge: 0.01, lasso: 0.16)

- No evidence of trained model exhibiting overfitting, as Mean Absolute Error (MAE) on ‘Testing’ data ($36,360) is in fact slightly lower than that from the ‘Training’ data ($36,650)

- With reference to the ‘Testing’ results, our model:
  - Explains ~ 89% of the variation in resale price (R-squared)
  - Has a Mean Absolute Error (MAE) of ~$36,000
  - Has a Mean Absolute Percentage Error of ~8.6%

6. Discussion / Suggestions for Further Research

(a) Summary of Results & Potential Use Cases

Features Most Strongly Associated with Resale Price

Expectedly and from a practical standpoint, features found to be most strongly associated with resale price are:

- ***Apartment Characteristics*** Exceptional Flat Types, Flat's Floor Area, Flat's Remaining Lease Years
- ***Public Transport Connectivity*** Proximity to an MRT Station, Nearest MRT Station Being a Public Transport Hub
- ***Travel Cost to the CBD via the MRT Network***
- ***Town-level Unobserved Features***

These insights might be utilised in the following ways by different stakeholders, as follows:

Home Buyers	**Guide search for a suitable apartment** *For example, if a home buyer's budget is constrained, he/she could focus on:* *(a) towns associated with lower resale prices (e.g., Sembawang, Chua Chu Kang), and* *(b) apartments further away from the nearest MRT station*
Home Owners	**Form expectations regarding resale value enhancement / degradation** *E.g., stemming from announcement of public works (new MRT station construction), remaining lease decay*
Policy Makers	**Consider studying if regional economic centre development plans should be enhanced** *As travel cost penalty to the CBD via the MRT network does not diminish significantly at the network's tail ends, attractiveness of regional economic centres could be studied, with greater economic decentralisation in mind*

6. Discussion / Suggestions for Further Research

(a) Summary of Results & Potential Use Cases

Predictive Ability of the Resale Price Model

- Has a Mean Absolute Error (MAE) of ~$36,000
- Has a Mean Absolute Percentage Error of ~8.6%

The predictive model could be used by:

Home Buyers / Home Owners	**To assess what an apartment's fair value might be** *However it should be noted that the model is, strictly speaking, valid within the time period analysed (2012-21)* *Forming estimates at later time periods should ideally be performed by refitting the model with more current data*

(b) Suggestions for Further Research

To consider including other features, such as:

- Proximity to green spaces (e.g., parks, nature reserves)
- Environmental quality (e.g., air quality, ambient noise levels)
- Proximity to industrial estates (e.g., by industrial type – heavy / light)

As these could lend further insight on attributes (not) valued by homeowners, and aid with urban planning cost/benefit analyses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Additional Slides

7. Appendix

- Appendix A: Utilising Unregularised (Instead of Regularised) Regression Modelling for Inference
- Appendix B: Other Features Associated with Resale Price

8. References

7. Appendix A : Utilising Unregularised (Instead of Regularised) Regression Modelling for Inference

Regularisation (ridge/lasso) has not been utilised for this purpose, as the approach produces biased coefficient estimates – which stem from:

(a) Regularisation inherently biasing coefficient estimates towards zero

- i.e., accepting greater model bias in exchange for lower variance - with the view towards increasing a model's generalisability in a prediction context [11]

(b) Risk of introducing omitted variable bias (OVB) when lasso regularisation is applied

- While the approach can aid with feature selection (as it allows coefficient shrinkage to reach zero) - features that are subsequently dropped (i.e., features with coefficient estimates = zero) may be associated with the remaining feature(s) and outcome, resulting in the remaining feature(s)' coefficients being affected by OVB
- While OVB is not a concern in the context of prediction, it is the context of inference - as OVB can lead to over/underestimation of a coefficient's magnitude [12]

7. Appendix B : Other Features Associated with Resale Price (1)

The following features were found to be associated with resale price, albeit not as strongly as features discussed earlier. The results herein may nonetheless be of interest:

(1) Proximity to Malls / Hawker Centres

- Being located within (as opposed to being beyond) 1km of a mall (hawker centre) commands a price premium between $4,500 to $9,000 ($7,100 to $19,000), depending on proximity and holding other features constant
- Resale prices are on average $15,000 higher if the nearest hawker centre is large (i.e., has more than 100 food and market stalls), as opposed to being small

(2) Proximity to 'Branded' Schools

- The average number of 'branded' primary (secondary) schools within 1km of a resale flat stands at less than 1 (0.5, 0.4)
- An additional 'branded' primary (secondary) school within this radius is estimated to command a price premium of $5,300 ($9,600), holding other features constant
- A potential reason why the price premium on 'branded' schools is not higher could be due to 'branded' school effects being more pronounced among private-property transactions instead - where willingness-to-pay is likely higher among this group of higher-income home buyers

7. Appendix B ： Other Features Associated with Resale Price (2)

The following features were found to be associated with resale price, albeit not as strongly as features discussed earlier. The results herein may nonetheless be of interest:

(3) Within Block Neighbours

- The presence of rental units within a block is associated with a price penalty of $11,000 on average, and holding other features constant
- This is consistent with reports of residents preferring to live a distance away from rental unit (i.e., low-income) residents [13]
- From a policy perspective, the presence of the penalty is concerning as this might be due to:
  - Undue stigmatisation
  - Social issues associated with 'rental' unit residents that have spillover effects on neighbours
- Understanding the underlying cause(s) of the penalty could thus aid with developing interventions to address them

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