Residential Property Prices in Singapore

Table of Contents

Introduction	3
Methodology	3
Results and Discussion	3
Dataset	3
Features	3
Engineered Features	3
Excluded Features	4
Assumptions	4
Exploratory Data Analysis	5
Continuous Features	5
Categorical Features	6
Modelling	9
Data Preparation	9
Model Training	9
Model Evaluation	9
Feature Importance	9
Strategies To Curb Housing Price Inflation	10
Raise the cost of borrowing	10
Increase housing supply	10

Introduction

In recent years, residential property prices in Singapore have increased significantly. Curbing this price inflation is important to maintain the affordability of housing in Singapore. This forms the basis of this study, which aims to identify the factors affecting residential property prices in Singapore and to formulate strategies to curb price inflation.

Methodology

Feature exploration and engineering was first performed. Thereafter, feature exclusion was performed. This was followed by exploratory data analysis and model training, evaluation and interpretation.

Results and Discussion

Dataset

The dataset used in this study consisted of HDB resale transactions from the years 1990 to 2020.

Features

The following features were present in the dataset:

Feature	Туре	Description	
month	string	When the sale occurred in YYYY-MM format.	
town	string	Town that the property was located in, e.g., BUKIT	
		TIMAH.	
flat_type	string	Flat type, e.g., 4 ROOM.	
block	integer	Block number of the property.	
street_name	string	Street name that the property was located on.	
storey_range	string	Approximate floor level of the property, e.g., 04	
		TO 06.	
floor_area_sqm	integer	Floor area of the property in square metres.	
flat_model	string	Model of the flat, e.g., IMPROVED.	
lease_commence_date	string	Date of lease commencement for the property.	
resale_price	integer	Price that the property sold for.	

Engineered Features

The following features were engineered:

Feature	Туре	Description	
year	integer	Calendar year in which the sale occurred.	
remaining_lease	integer	Number of years remaining on the property lease	
		at the time of the sale.	
storey	integer	The approximate floor level of the property,	
		calculating by averaging the range provided, e.g.,	
		04 TO 06 will be processed to be 5.	

Excluded Features

The following features were excluded from further analysis:

Feature	Reason	
month	Replaced by the engineered year feature.	
storey_range	Replaced by the engineered storey feature.	
lease_commence_date	Replaced by the engineered remaining_lease feature.	
block	Assumed to have no impact on property prices.	

Assumptions

- 1. HDB resale transactions represents the sale of all residential properties in Singapore.
- 2. The initial lease for all properties is 99 years.
- 3. The flat_types of 1 ROOM, 2 ROOM, 3 ROOM, 4 ROOM, 5 ROOM, EXECUTIVE, MULTI-GENERATION have ascending floor areas on average, i.e., an average 4 ROOM flat is bigger than an average 3 ROOM flat.
- 4. Each street_name can only be part of one town.
- 5. Block numbers have no impact on property prices.
- 6. Buyers can finance their property purchase with either a bank loan or a HDB housing loan, with the latter interest rate set at 0.1% above the prevailing Central Provident Fund Ordinary Account interest rate.

Exploratory Data Analysis

Continuous Features

The following table outlines the Pearson and Spearman correlation coefficients of the features with resale prices.

Feature	Correlation Coefficient		
	Pearson	Spearman	
floor_area_sqm	0.625	0.656	
year	0.605	0.598	
storey	0.212	0.13	
remaining_lease	-0.013	0.036	

Both features of floor_area_sqm and year were observed to have significant positive correlation with resale prices. This observation is intuitive as larger properties can be expected to sell for more. In addition, due to inflation, resale prices are expected to rise over time. Hence, these two features are likely to be influential on property prices.

Mean resale prices over the years for All flat types in All towns.

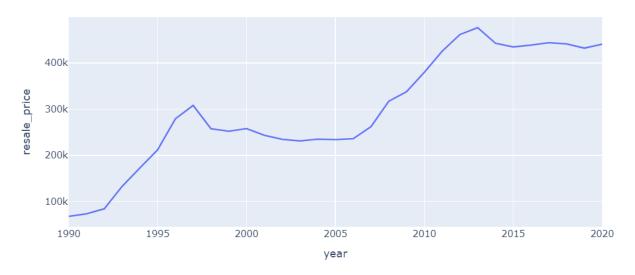


FIGURE 1: PLOT OF MEAN RESALE PRICES OVER TIME

Categorical Features

Town

It was observed that mean resale prices differed significantly across the various towns, with towns like 'BISHAN', 'BUKIT TIMAH' and 'PUNGGOL' having high mean resale prices.

Mean resale prices by town.

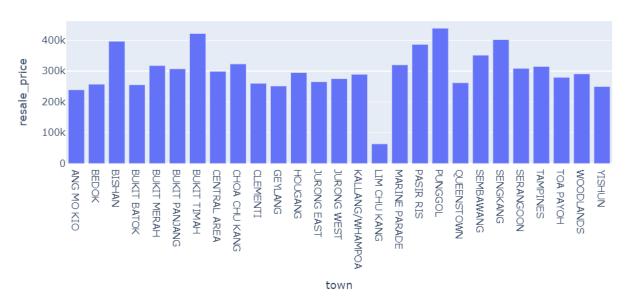


FIGURE 2: MEAN RESALE PRICES BY TOWN.

Street Name

It was observed that mean resale prices also different significantly across the various street names. However, due to the large number of streets (568) and the assumption that each street can only be part of one town, it is likely that the town feature is more influential on property prices.

Mean resale prices by street_name.



FIGURE 3: MEAN RESALE PRICES BY STREET NAME (NOT ALL STREET NAMES DISPLAYED).

Flat Type

It was observed that there was a clear and significant influence of the flat type on property prices. This is supported by the assumption that the flat types presented in Figure 4 have ascending floor areas on average, and that larger properties tend to sell for higher prices.

Mean resale prices by flat_type.

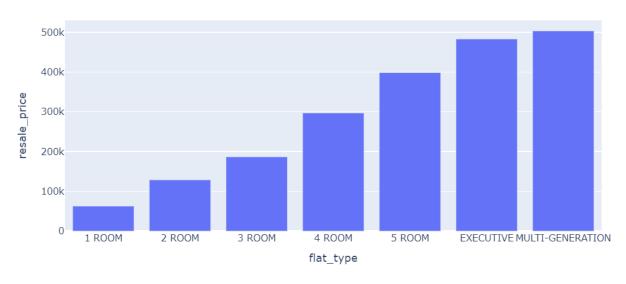


FIGURE 4: MEAN RESALE PRICES BY FLAT TYPE.

Flat Model

It was observed that the flat model influenced property prices. However, given that one flat model can be present in multiple flat types, e.g., the 'IMPROVED' flat model is present in the 1 ROOM to 5 ROOM flat types, it is likely that the flat type is more influential on property prices.

Mean resale prices by flat_model.

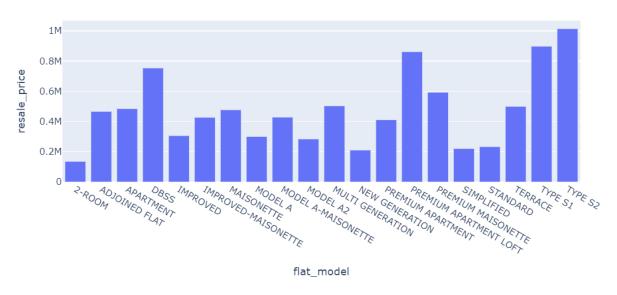


FIGURE 5: MEAN RESALE PRICES BY FLAT MODEL.

Modelling

Data Preparation

The dataset was split into training and test datasets by year, with the training dataset including transactions from the year 1990 to 2018, and the test dataset including transactions from the year 2019 to 2020.

Model Training

A CatBoost model was trained using the training dataset. Hyperparameter tuning was performed to identify the most optimal hyperparameters using the inbuilt grid search function of CatBoost.

Model Evaluation

The trained model was evaluated against the test dataset, with the evaluation metric being the mean absolute percentage error (MAPE). The test set MAPE was calculated to be 5.8%, meaning that across the entire test set, the predicted resale price was, on average, within +- 5.8% of the actual resale price.

Feature Importance

The top 4 most important features of year, floor_area_sqm, flat_type and town had an overwhelming impact of 86% on the predictions, with the remaining 14% split between street_name, flat_model, remaining_lease and story. Of the top 4 most important features, year stood out as the most important feature at 35%, 13.7%-points higher than the next most important feature of floor_area_sqm at 21.3%. flat_type and town had similar feature importances at 15.4% and 14.3% respectively.

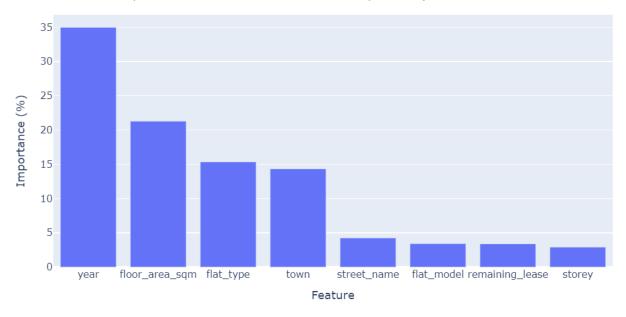


FIGURE 6: MODEL FEATURE IMPORTANCE

Strategies To Curb Housing Price Inflation

Raise the cost of borrowing

The year feature was identified to be the most influential feature on property prices. While it is not possible to directly influence the year, i.e., it is not possible to retrospectively purchase a property at a lower price, the underlying inflation that resulted in this observation was be influenced.

The assumption is that buyers can finance their property purchase with either a bank loan or a HDB housing loan, with the latter interest rate set at 0.1% above the prevailing Central Provident Fund Ordinary Account interest rate.

Therefore, if the interest rate charged by banks on a property loan is higher than that charged in the HDB housing loan, raising the interest rate charged in the HDB housing loan is likely to moderate the effects of inflation on property prices. Care should be taken not to increase interest rates too much or too quickly as this could destabilise the housing market.

Increase housing supply

Property prices are the function of supply and demand. By increasing the supply of properties of in-demand flat types with highly desired floor areas, located in popular towns, housing price inflation is likely to be curbed.