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**PREDICTIVE FINANCIAL MODELLING**

**CA2: PREDICTING PERTH HOUSE PRICES**

**MODULE CODE: B9FA102**

**STUDENT NAME: YASIN GUNER**

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# CA2 – PART 1: PREDICTING HOUSING PRICES/REGRESSION

## Introduction

The analysis of the multiple linear regression results of Perth housing prices for Kaggle Proportion is discussed in this report. As the need for accurate housing market forecasting increases, the model determines drivers of property prices in Perth. Four independent variables are analysed: propose that useable land area and building floor area, latitude and longitude should be used to determine property values, as they all have some relation to economic characteristics affecting property values. This class of variables is analysed in the report with regard to relationships between the variables as well as their influence on property price volatility in Perth. Details of the observations seek to assist in the understanding of patterns in the housing market and the causes of price fluctuations.

## Methodology

In this particular research, multiple linear regression incorporated in Excel was used to examine the recent house prices in Perth. The set of data preparation activities included variable construction and handling of missing values. The dependent variable, house price, was examined against four key independent variables: area, floor, geographical coordinates, latitude and longitude, land (Mio et al. 2020). It offers understanding of how each of the variables affects price forecasts thus making the model most appropriate for this analysis and it gives insight into the behaviour of the Perth residential real estate market.

## Hypotheses

The relationship between house prices and independent variables was examined using the following hypotheses:

* **H0:** Perth house prices show no correlation with land area, floor area, latitude, and longitude.
* **H1:** There is a positive correlation between land area and house prices.
* **H2:** A positive correlation exists between floor area and house prices.
* **H3:** Geographic location variables, including latitude and longitude, significantly correlate with house prices.

These hypotheses form the basis of analysis of how each of the variables influences the property prices in Perth.

## Regression Model Analysis

This study sought to develop a home-price model with the house price as the dependent variable and the land area, the floor area, the latitude, and the longitude as the independent variables being regressed utilising the multiple linear regression technique.



**Table 5: Regression Statistics**

(Source: Refer to Excel)



**Table 6: ANOVA**

(Source: Refer to Excel)



**Table 7: Coefficient**

(Source: Refer to Excel)

The regression test gave an R-squared of 0.3278 which indicates that the independent variables used in the analysis produce 32.78% test on the price variation of the houses. On one hand, with this value, it is possible to conclude that the developed model focuses on a significant subset of the factors affecting house prices; on the other hand, there are probably other influential factors, including market conditions, property age, or specific neighbourhood characteristics that are not considered in the model (Yan and Aasma, 2020).

The coefficients show important information with respect to the correlations between house prices and independent variables. Floor area turns out to have a highly statistically significant impact with a coefficient of 2651.02 and near zero p-value for it. This result indicates that the use of the indoor space has the most effect on the value of the property. In the same manner, a positive relationship exists between the land area and house prices as its coefficient of 0.8981, significant at p<0.05, indicates added value of size of the land.

Geographic coordinates exhibit mixed effects: The economic importance of the latitudes shows that the coefficient for latitudes = 25819.99 with p<0.05, premium neighbourhoods are normally in the northern latitudes while the coefficients for longitudes = -493040.86 with p=0.0005 revealing that properties in the western latitudes are less desirable. There is strong evidence for the model, F-statistic (p=0). Though, there is moderate R-squared, it means that model performance can be optimised further. The research completes its analysis successfully to ascertain some of the determinants of house prices; for subsequent researches while designing the models for house price prediction, general extra factors can be included.

## Analysis and Interpretation of Results

The regression analysis provides critical insights into the influence of independent variables on Perth house prices:

**Land Area**: Land area also increases house prices as indicated by the coefficient 0.8981 having a highly significant p-value (1.66e-20). This expectation is as expected since the price per acre is adjusted according to potential investors’ perceived capacity to develop or expand upon the land.

**Floor Area**: With a larger positive coefficient of 2651.02 and highly statistically significant, floor area stands out as the most significant factor of the model. This result corroborates that increased interior dimensions increase property value since they fit the needs of a family unit or more amenities or merely more space (Chen et al., 2021).

**Latitude**: The result shows that latitude has significant positive effect on House Prices with a coefficient estimate of 25819.999 and p-value of 0.0041. This implies that houses in the northern localities may be in the noble areas, thus can attract premium property value (Rezaei, Faaljou, and Mansourfar, 2021).

**Longitude**: Longitude was found to have a negative influence on house prices; the coefficient was -493040.86, while the p value was less than 0.05. Moving to the west side of the city, the properties are not as expensive, probably due to strategic markets and necessities, goods and services, are more accessible in the east of Buchanan, near the business area.

What emerges from these results is the fact that these variables play some role in the determination of property price. The model’s R-squared of 0.3278 means that selected factors account for 33% of variation in house prices, the Adjusted R-squared signifies that model is sound. But other factors arising from the market, such as market changes or property age, may also affect prices as there are other drivers beyond such quantitative metrics (Ampomah, Qin, and Nyame, 2020).

## Conclusion

This research thus supports the hypothesis that, floor area, land area and geographic location, affect house prices in Perth. Density increases the prices because a larger surface area of the built structures translate to higher prices of the property and a larger piece of land also leads to higher prices of the buildings. There is also a positive significance of latitude while a negative one of longitude depending on people’s preferences as to location of houses. Despite the relatively low R-squared value it indicates that there is potential for future growth while the model provides an overview of important pricing factors. Future studies should include other factors that help to paint the specific picture of the influence of market tendencies and properties characteristics for the benefit of the stakeholders of the real estate market.

# CA2: PART 2: PORTFOLIO OPTIMIZATION

## i) Expected Return of Portfolio

Portfolio management has emerged as a key to delivering assets and protecting or enhancing investor value for the specific objectives of wealthy individuals and institutions.



**Part 1: Expected Return Calculations**

(Source: Refer to Excel)

This first portfolio pointed to an investment split with equal proportion in three sectors so as to facilitate diversification and show potential investors’ return. The total investment of €44,000,000 is distributed as follows: €25,000,000 of technology companies based in the USA, €11,000,000 of Japanese based financial service companies, €8,000,000 in travel and adventure-based South Africa. It is expected that these investments will bring €2,600,000, €2,000,000, and €4,000,000 of cash inflows. These same expected cash inflows are to be derived from non-current financial assets in the consolidated balance sheet of BOM. Based on the proposed total expected cash flow of € 8, 600,000 the expected portfolio returns stands at 19.55%. Of the sectors, the South African travel company generates the highest returns among the sectors in relation to its capital investment.

## ii) Risk assessment of two assets portfolio



**Part 2: Risk Evaluation of 2 Assets Portfolio**

(Source: Refer to Excel)

In the second part, risk assessment was conducted for a portfolio containing two assets: one will be sixty zero five forty million euros and the other will be sixty zero five thirty million euros. These assets had varying probabilities of returns across three scenarios: Here are the following outcomes by solving the problems: best, expected and worst.

### a) Calculations of variance and standard deviation of each asset

This expected return for Asset 1 was 8.3% with the total risk as measured by standard deviation at 2.73% which could be regarded as moderate risk. On the other hand, Asset 2 had expected return of 10.2 percent and the standard deviation of 5.47 percent, in line with higher risk level. These figures show a risk-return relation in the financial investments to be made.

### b) Calculation of Standard Deviation of Portfolio

The researcher analysed risk on the portfolio with the correlation between two assets being 0.77. This certainly indicates that the assets move in the same direction to a large extent and consequently, the overall risk of the portfolio is given a boost. The portfolio standard deviation was found through a simple weighted average of the individual assets standard deviations yielding a value of 4.28%. That corroborates the rationale of diversification gains even whenever the assets display a very low positive covariance (Zhang et al., 2020). Lastly, an intermediate risk applying the time value of money is 4.28% which gives a balance between Asset 2 and Asset 1 providing acceptable volatility in the portfolio.

## iii) Portfolio optimization in excel using variance covariance approach

The variance covariance method is useful for optimising a portfolio by either taking for maximum returns from it or for using it to minimise risk in a portfolio taking into account constraints such as required sum of weights being equal to one and weights being non-negative. It also enables alteration like capping the standard deviation or the floor and ceiling that returns have to touch (Xidonas et al. 2020). For example, if an investor wants to take 4 percent risk, the covariance approach may provide optimal weights for increase in profitability. The analysis of sector-based portfolio revealed an impressive 19.55% return through diversification and the second one demonstrated impacts of correlation with standard deviation of 4.28% to provide expectant returns as well as protection from risk for ultimate wealth creation.

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