Iteratively Reweighted Least Squares-based Generalized Linear Model for Assessing the Impact of Macroeconomic Indicators on Property Investment

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Abstract

This study explores the impact of macroeconomic indicators on Net Present Value (NPV) in the Malaysian property sector from 2010 to 2022. Using data from Sharia-compliant property firms, Generalized Linear Models (GLMs) and logistic regression analyze Consumer Price Index (CPI), Gross Domestic Product (GDP), interest rate (IR), and exchange rate (ER) effects on NPV. Significant positive associations are found for CPI (coefficient = 0.028, p = 0.001) and GDP (coefficient = 0.004, p = 0.045), indicating higher

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inflation and economic growth enhance NPV. Conversely, ER (coefficient = −0.015, p = 0.003) and IR (coefficient = −0.042, $p < 0.001$) negatively impact NPV, reflecting currency volatility and borrowing costs. GLM-IRLS models show robust predictive power (Deviance = 235.67, R-squared = 0.30), informing strategic decision-making for property investments amid economic fluctuations.

Keywords: Net present value, generalized linear models, logistic regression, macroeconomic indicators, iteratively reweighted least square, investment property, real estate.

1 Introduction

Property investment is a dynamic field that is significantly influenced by various economic indicators. Understanding and predicting these indicators can provide crucial insights for investors, helping them make informed decisions and optimize their investment strategies. One effective method for modeling and forecasting economic indicators is through the use of Generalized Linear Models (GLMs). GLMs extend traditional linear models, accommodating a wider range of data distributions and relationships between variable [1–3].

Over the last decade, Generalized Linear Models (GLMs) have become a common statistical tool for modeling actuarial data. The main merits of GLMs are twofold. Firstly, regression is no longer restricted to normal data but is extended to distributions from the exponential family. This enables appropriate modeling of various types of data, such as frequency counts, skewed distributions, or binary outcomes. Secondly, a GLM models the additive effect of explanatory variables on a transformation of the mean, instead of the mean itself [4, 5]. Traditional linear models often fall short in capturing the complexities and inherent variability within economic data. GLMs provide a more flexible and powerful approach to analyzing economic indicators, making them particularly suitable for complex economic and financial data, such as those found in property investment analysis.

In the context of investment return, GLMs can effectively model how economic indicators like CPI, GDP, and exchange rates affect the NPV of investments. By allowing for different types of data distributions, GLMs provide a flexible and robust framework for capturing the complex, non-linear, and potentially heteroscedastic relationships between these indicators and investment outcomes [6]. This capability is crucial for accurately reflecting the dynamics of property investments influenced by various economic factors. By leveraging the flexibility and robustness of GLMs, stakeholders can gain deeper insights into the economic dynamics at play, leading to more informed and effective investment strategies. GLMs enable a more nuanced understanding of how explanatory variables impact investment outcomes, ensuring that the model accurately reflects the real-world complexities of the investment sect.

This study addresses these challenges by incorporating Iteratively Reweighted Least Squares (IRLS). IRLS is a robust method that iteratively adjusts weights and parameter estimates to minimize the weighted sum of squared residuals [7]. This approach enhances the reliability and accuracy of estimates, particularly in the presence of heteroscedasticity and outliers. Incorporating IRLS represents a significant contribution of this study, allowing for more robust modeling of property investment dynamics and economic indicators.

The property investment sector relies heavily on economic indicators such as the Consumer Price Index (CPI), Gross Domestic Product (GDP), and exchange rates to evaluate Net Present Value (NPV). However, accurately modeling the complex, non-linear, and potentially heteroscedastic relationships between these indicators and investment outcomes poses significant challenges. Traditional linear models often fail to capture these complexities, necessitating more flexible and robust statistical approaches. The combined use of Generalized Linear Models (GLMs) and Iteratively Reweighted Least Squares (IRLS) for analyzing economic indicators in the property sector remains underexplored. This study addresses this gap by applying the GLM-IRLS approach to provide nuanced insights into the determinants of property investment returns. The study focuses on applying Generalized Linear Models (GLM) and the Iteratively Reweighted Least Squares (IRLS) technique to empirically examine the relationship between key macroeconomic indicators—specifically CPI, GDP, interest rate (IR), and exchange rate (ER)—and investment profitability in the Malaysian property development sector. Using data from 62 Sharia-compliant property firms spanning 2010 to 2022, the study aims to: (1). Analyze the impact of CPI, GDP, IR and ER on NPV of property investments from 2010 to 2022 using Generalized Linear Models (GLM) and logistic regression; (2). Evaluate the predictive accuracy of GLM-IRLS in modeling NPV based on CPI, GDP, IR, and ER, using metrics such as Deviance, AIC, BIC, and R-squared values; (3). Provide strategic insights derived from empirical findings on the influence of macroeconomic factors on NPV to guide stakeholders and policymakers in the property sector.

2 Materials and Methods

Generalized Linear Models (GLM), established by Nelder and Baker [8] and refined by [9], extend linear regression models by allowing the response variable to follow different distributions and using a link function to relate the predictor to the mean. This flexibility makes GLMs suitable for various types of data, including binary, count, and continuous outcomes. Emphasis is placed on logistic regression within GLM to reveal the complex relationships between economic indicators and NPV, with subsequent sections detailing model application and goodness of fit assessment. The purpose of the general linear regression approach is to model the relationship that exist between a response variable (dependent variable) y, against two or more explanatory variables (independent variables) x_i. The general form for the multiple linear regression equation is,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i + \varepsilon_i \tag{1}$$

where β are the regression coefficients which will be estimated using the maximum likelihood estimator. The i is the number of regressor variables and ε is the error term. It can be presented in matrix form with *n* number of observations as follows,

$$y = x_i \beta + \varepsilon. \tag{2}$$

Equation (2) can be presented in matrix form as follows

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & \cdots & x_{1i} \\ 1 & x_{21} & \cdots & x_{2i} \\ \vdots & \vdots & \cdots & \vdots \\ 1 & x_{n1} & \cdots & x_{ni} \end{pmatrix} + \begin{pmatrix} \beta_0 \\ \beta_2 \\ \vdots \\ \beta_i \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} \tag{3}$$

The study aims to analyze correlations in datasets that deviate from normal distribution assumptions. General Linear Models (GLMs) extend beyond traditional models by using exponential distributions and a link function. The link function connects the linear predictor to the mean of the response variable's distribution, ensuring it falls within the correct range. This allows GLMs to handle various data types, such as binary, count, and continuous outcomes, making them suitable for discrete or non-normally distributed variables. GLMs provide a unified framework, relaxing restrictive assumptions and offering robust methods for diverse data analysis.

$$E(Y|X) = X^T \beta \tag{4}$$

And hence, we arrive at the following model.

$$E(y) = \mu = g^{-1}(\eta) \tag{5}$$

The GLM approach involves specifying the distribution, determining the connection/link function $(\cdot)$, and selecting the explanatory variables (linear predictor).

2.1 The Random Component: The Exponential Family

In a GLM, the response variable is treated as a random variable with a probability distribution that is considered to be a member of the exponential distribution family, which includes Gaussian, Bernoulli, gamma, Poisson, and numerous other well-known distributions as special instances. The usual linear-exponential form as follows:

$$f(y;\theta,\varphi) = \exp\left[\frac{y\theta - b(\theta)}{a(\varphi)} + c(y,\varphi)\right] \tag{6}$$

In this study, $a(\cdot)$, $b(\cdot)$, and $c(\cdot)$ stand as functions varying across different exponential family distributions, outlining the probability-density function for continuous random variables, or the probability mass function for discrete ones. Meanwhile, θ and φ signify the canonical and dispersion parameters of the exponential family, respectively. Expanding further, for the exponential distribution, the expected value of a random variable Y is expressed as:

$$E(Y) = \mu = b'(\theta) \tag{7}$$

and the variance is presented as follows,

$$Var(Y) = b''(\theta)a(\varphi) = \mu'(\theta)a(\varphi) \tag{8}$$

The expressions for the mean and variance described above are derived from the log-likelihood function of the exponential distribution family and its differentials.

$$\frac{\partial l(\theta,\varphi;y)}{\partial\theta} = \frac{\partial l}{\partial\theta}\left(\frac{y\theta - b(\theta)}{a(\varphi)} + c(y,\varphi)\right) = \frac{y - b'(\theta)}{a(\varphi)} \tag{9}$$

where,

$$l(\theta,\varphi;y) = \log f(\theta,\varphi;y) \tag{10}$$

and consequently

$$\frac{\partial^2 l(\theta,\varphi;y)}{\partial\theta^2} = -\frac{b''(\theta)}{a(\varphi)} \tag{11}$$

Moreover, according to the theory of MLE, we know the following expressions:

$$E\left(\frac{\partial l}{\partial\theta}\right) = 0 \tag{12}$$

and

$$E\left(\frac{\partial^2 l}{\partial\theta^2}\right) + E\left(\frac{\partial l}{\partial\theta}\right)^2 = 0 \tag{13}$$

Then the following is obtained for the expected value and the variance respectively as follows,

$$E(Y) = \mu = b'(\theta) \tag{14}$$

$$Var(Y) = b''(\theta)a(\varphi). \tag{15}$$

Thus, it has been demonstrated that the aforementioned relations hold. The variance function is frequently expressed as $(\mu) = b''(\theta)$, indicating the dependency between the mean and the variance [10].

2.2 The Link/Connection Function

The link function $(\cdot)$ need to be a monotone, differentiable function used to relate the expected value of the dependent variable Y to the predictors $x_1, x_2, x_3, \ldots x_p$. Equation (16) represents the expected value of the response variable Y, which is a function of the linear predictor η presented as follows.

$$E(Y_i) = \mu_i \tag{16}$$

Equation (17) provide that the link function $g(\mu)$ relates the linear predictor η to the expected value μ of the response variable as follows.

$$g(\mu_i) = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_k = x_i'\beta \tag{17}$$

Equation (18) present the inverse function $g^{-1}(\cdot)$, which is used to relate the expected value μ back to the linear predictor η.

$$E(Y_i) = g^{-1}(\eta_i) = g^{-1}(x_i'\beta) \tag{18}$$

Since it establishes the relationship between the response variable's expected value and the linear predictor, the link function selection is essential to GLMs. For there to be a correct relationship between the linear predictor and the expected value, the link function has to be differentiable and monotonic [11]. The following is the inverse function for a monotone function,

$$g^{-1}(g(\mu)) = \mu \tag{19}$$

The type of link function to be used depends on the data used [11, 12].

2.3 Maximum Likelihood Estimation of Model

In a GLM, the likelihood function $L(\beta)$ for parameters β given the data (y_i, X_i) is expressed as follows:

$$L(\beta) = \prod_{i=1}^{n} f(y_i; \theta_i, \phi) \tag{20}$$

where $f(\cdot)$ is the probability density function or probability mass function of the response variable (y_i), (θ_i) are the mean parameters related to the linear predictor $\eta_i = X_i^\top \beta$, and (ϕ) represents any dispersion parameters.

The log-likelihood function $\ell(\beta)$ is as follows:

$$\ell(\beta) = \sum_{i=1}^{n} [y_i \eta_i - b(\eta_i) + c(y_i)] \tag{21}$$

where $b(\cdot)$ and $c(\cdot)$ are functions related to the distribution's properties. The goal of MLE is to find $\hat{\beta}$, the estimator of β, by maximizing $\ell(\beta)$:

$$\hat{\beta} = \arg\max_{\beta} \ell(\beta) \tag{22}$$

This typically involves iterative methods like Newton-Raphson or Fisher scoring due to the complexity of the log-likelihood function.

2.3.1 Logistic regression model (binomial family)

Logistic regression is a specific case of GLM used for binary classification. The model assumes the response variable Y_i follows a Bernoulli distribution, where $P(Y_i = 1) = \pi_i$ and $P(Y_i = 0) = 1 - \pi_i$.

The linear predictor η_i in logistic regression is linked to the probability π_i through the logit function as follows,

$$\eta_i = X_i^\top \beta \tag{23}$$

$$\pi_i = \frac{1}{1 + e^{-\eta_i}} = \frac{1}{1 + e^{-X_i^\top \beta}} \tag{24}$$

The log-likelihood function for logistic regression is:

$$\ell(\beta) = \sum_{i=1}^{n} [y_i X_i^\top \beta - \log(1 + e^{X_i^\top \beta})] \tag{25}$$

The gradient $\nabla \ell(\beta)$ and Hessian matrix $H(\beta)$ are crucial for MLE:

$$\nabla \ell(\beta) = X^\top (y - \pi) \tag{26}$$

$$H(\beta) = X^\top W X \tag{27}$$

where W is a diagonal matrix with elements $(\pi_i(1 - \pi_i))$.

Maximum Likelihood Estimation provides robust parameter estimates in GLMs and logistic regression, essential for modeling relationships between predictors and binary outcomes.

2.4 Iteratively Reweighted Least Squares (IRLS)

When dealing with weighted least squares problems with non-constant error variances, the IRLS approach is a powerful optimization tool that is applied in statistical estimation. The IRLS is a frequently used technique [13]. It works well with models that have non-Gaussian error distributions or heteroscedastic errors. The weighted sum of squared residuals is minimized by the IRLS algorithm, which iteratively estimates model parameters [7]. At each iteration, the IRLS method updates the parameter estimates by solving a weighted least squares problem. Let's denote the observed data as (x_i, y_i), where x_i represents the predictor variables and y_i represents the response variable. The model to be estimated is given by

$$y_i = f(x_i; \beta) + \epsilon_i \tag{28}$$

where $f(x_i; \beta)$ is the model function with parameters β and ϵ_i is the error term.

The weighted sum of squared residuals to be minimized is defined as:

$$Q(\beta) = \sum_{i=1}^{n} w_i (y_i - f(x_i; \beta))^2 \tag{29}$$

Here, w_i represents the weights assigned to each observation i. In the IRLS method, the weights are adjusted iteratively based on the residuals from the previous iteration.

The weight (w_i) are typically derived from the derivative of a loss function, such as the Huber loss or Tukey's biweight function, which are robust estimators. The IRLS algorithm updates the weights and parameter estimates using the following steps:

Step 1: Initialization

Start with an initial guess $\beta^{(0)}$.

Step 2: Iterative Process

Update Linear Predictor: Compute the linear predictor for each observation i using Equation (30) as follows

$$\eta_i^{(t)} = X_i^\top \beta^{(t)} \tag{30}$$

Compute Weights: Compute the weights using Equation (31) as follows,

$$w_i^{(t)} = \frac{1}{V(\mu_i^{(t)})}, \tag{31}$$

where $V(\mu_i^{(t)})$ is the variance function related to the chosen distribution and link function.

Adjusted Response: Adjust the response using Equation (32) as follows

$$z_i = \eta_i^{(t)} + \frac{y_i - \mu_i^{(t)}}{V'(\mu_i^{(t)})}, \tag{32}$$

where $(V'(\mu_i^{(t)})$ is the derivative of the variance function.

Update Parameters: Update β using weighted least squares based on Equation (33):

$$\beta^{(t+1)} = (X^\top W^{(t)} X)^{-1} X^\top W^{(t)} z \tag{33}$$

where $W^{(t)}$ is a diagonal matrix of weights $w_i^{(t)}$.

Step 3: Convergence

Repeat Steps 2 until convergence criteria are met (e.g., small change in β or maximum number of iterations reached).

The convergence is often assessed by the Euclidean distance or the maximum absolute difference [14] between parameter vectors $\beta^{(t)}$ and $\beta^{(t+1)}$:

$$\|\beta^{(t+1)} - \beta^{(t)}\| < \epsilon \tag{34}$$

where ϵ is a small threshold, typically representing the convergence tolerance.

The convergence criterion in IRLS for GLMs ensures that parameter estimates stabilize sufficiently across iterations, indicating that further iterations are unlikely to significantly change the estimates. This approach balances computational efficiency with accurate parameter estimation, making it a cornerstone in statistical modeling and inference.

Algorithm 1 Iteratively reweighted least squares (IRLS) for GLMs

procedure IRLS_GLM$X, y, \mu, V, V', \epsilon, max_iter$
  Initialization:
  $\beta^{(0)} \leftarrow$ Initial guess of parameters
  $t \leftarrow 0$ ▷ Iteration counter
  while $t < max\_iter$ **do**
    Step 1: Compute linear predictor:
    $\eta^{(t)} \leftarrow X\beta^{(t)}$
    Step 2: Compute weights:
    $w_i^{(t)} \leftarrow \frac{1}{V(\mu_i^{(t)})}$ ▷ Using variance function $V(\cdot)$
    Step 3: Adjust response:
    $z_i \leftarrow \eta_i^{(t)} + \frac{y_i - \mu_i^{(t)}}{V'(\mu_i^{(t)})}$ ▷ Using derivative $V'(\cdot)$
    Step 4: Update parameters:
    $\beta^{(t+1)} \leftarrow (X^\top W^{(t)} X)^{-1} X^\top W^{(t)} z$
    $t \leftarrow t + 1$
    Step 5: Convergence check:
    Calculate change: $\Delta\beta \leftarrow |\beta^{(t+1)} - \beta^{(t)}|$
    if $\Delta\beta < \epsilon$ **then**
      break ▷ Convergence criteria met
    end if
  end while
  Output:
  return $\beta^{(t)}$ ▷ Estimated parameters
end procedure

2.5 Data Collection

This study examines the relationship between key macroeconomic indicators, specifically the Consumer Price Index (CPI), Gross Domestic Product (GDP), interest rate (IR), and exchange rate (ER) as independent variables, and the value of an investment in the Malaysian property development sector, measured by Net Present Value (NPV). The dataset use in this study comprises data from property companies adhering to Sharia compliance standards. NPV calculated using Equation (35) and (36) spanning from 2010 to 2022 based cash flow, discount rate, and the initial investment outlay extracted from the financial statements of these companies, sourced from the Bursa Malaysia website (*www.bursamalaysia.com*). The Economic indicators including GDP, CPI, exchange rates, and deposit interest rates for Malaysia were sourced from reliable institutions such as the Department of Statistics Malaysia (*www.dosm.gov.my*) and Bank Negara Malaysia (*www.bnm.gov.my*). These sources provide comprehensive and reliable data for our research involving GDP, CPI, exchange rates, and deposit interest rates in Malaysia.

The primary objective is to identify the determinants of NPV within the Malaysian property sector. Utilizing statistical techniques such as Generalized Linear Models (GLM) and logistic regression, we aim to discern the relationship between macroeconomic factors and profitability in the context of property investment in Malaysia.

2.6 Conceptual Framework

These objectives aim to deepen understanding of the macroeconomic drivers of NPV in property investments, validate modeling techniques using GLM-IRLS, and provide practical guidance for stakeholders navigating economic uncertainties in the sector. The relationship between investment returns in property sector and key macroeconomic factors: Consumer Price Index (CPI), Gross Domestic Product (GDP), Net Present Value (NPV), Interest Rate (IR), and Exchange Rate (ER). The central measure of success is evaluated through the Net Present Value (NPV) of these firms.

2.6.1 Net present value (NPV)

NPV is a critical metric in investment planning and capital budgeting, indicating the difference between present cash inflows and outflows over a specified period. It serves as a fundamental criterion for assessing project viability, with a positive NPV indicating favorable investment prospects [15, 16]. The formula for NPV involves discounting future cash flows at a predetermined rate:

$$NPV = \frac{CF_t}{(1+r)^t} - C_0 \tag{35}$$

Here CF_t is cash flow in period (t), r is the discount rate, T is the total number of periods and C_0 is the initial investment outlay (at time 0).

$$NPV = \sum_{t=0}^{T} \frac{CF_t}{(1+r)^t} - C_0 \tag{36}$$

By meeting these requirements and correctly applying the NPV formula, stakeholders can make informed decisions regarding investments, projects, or business opportunities based on their financial attractiveness and profitability.

2.6.2 Gross domestic product (GDP)

GDP measures the total value of goods and services produced within a country over a specified period. It serves as a comprehensive indicator of economic performance, capturing economic scale and growth. The GDP formula is:

$$\begin{aligned} GDP = {} & \textit{Consumer Spending} + \textit{Investment} + \textit{Government Spending} \\ & + (\textit{Exports} - \textit{Imports}) \end{aligned} \tag{37}$$

Increased national spending generally correlates with higher investment value in the property sector, potentially benefiting firms.

2.6.3 Consumer price index (CPI)

CPI reflects inflation by measuring changes in the price level of a basket of goods and services over time[17]. It is calculated as:

$$CPI = \left(\frac{\textit{Cost of Market Basket in Given Year}}{\textit{Cost of Market Basket in Base Year}} \right) \times 100 \tag{38}$$

While long-term inflation may not significantly impact costs due to concurrent increases in prices and wages, short-term wage rigidity can reduce consumption and investment returns.

2.6.4 Interest rate (IR)

IR represents the cost of borrowing or the return on investment. It influences investment decisions by affecting borrowing costs, investment attractiveness, and economic activity [18]. IR's general impact can be modeled as:

$$IR = \textit{Cost of Borrowing} - \textit{Rate of Return on Investments} \tag{39}$$

Fluctuations in IR can profoundly affect property investment profitability.

2.6.5 Exchange rate (ER)

ER denotes the value of one currency relative to another and impacts international trade and investment. It is expressed as:

$$ER = \frac{\textit{Value of Domestic Currency}}{\textit{Value of Foreign Currency}} \tag{40}$$

ER fluctuations can significantly influence investment returns, particularly for firms engaged in international transactions or exposed to currency risks.

2.6.6 Target variable: performance of malaysian property sector

This study aims to assess investment value in Malaysian property firms through the NPV metric, reflecting their financial viability and profitability.

2.6.7 Predictor variables

The study integrates CPI, GDP, NPV, IR, and ER into a generalized linear regression model, acknowledging potential correlations and multicollinearity problem among these variables. These predictors collectively provide insights into the complex interactions between macroeconomic dynamics and investment performance within the Malaysian property sector.

3 Results and Discussion

This section presents the results of the study, which examines the relationship between the Net Present Value (NPV) of property companies and key macroeconomic indicators from 2010 to 2022. The analysis focuses on Gross Domestic Product (GDP), Consumer Price Index (CPI), Exchange Rate (ER), and Interest Rate (IR), using Iteratively Reweighted Least Squares (IRLS) within the framework of Generalized Linear Models (GLMs) to model these variables.

Table 1 provides an overview of the relevant NPVs of the property sector with their basic statistical characteristics, spanning from 2010 to 2022. This 12-year period captures significant economic trends and offers insights into market conditions. The data for property companies and indices, including AMCOPRP, ARK, ASIAPAC, AYER, BDB, BKOON, CVIEW, CRESNDO, and ECOWOLD, reveals diverse mean values and varying ranges. Notably, AYER shows an increase in average value from 4.24 in 2010 to 4.44 in

Table 1 Descriptive Statistics of the NPV of Individual Investment Property (2010–2022)

Variable	Mean	Std Dev	Min	25th Percentile	Median	75th Percentile	Max
AMCOPRP	0.6346	0.2265	0.3	0.455	0.695	0.86	0.99
ARK	0.3019	0.1909	0.06	0.12	0.28	0.46	0.6
ASIAPAC	0.1415	0.0554	0.065	0.105	0.14	0.19	0.305
AYER	5.23	1.52	2.48	4.4	4.6	6.4	7
BDB	0.6372	0.2265	0.31	0.67	0.68	0.75	1.089
BKOON	0.24	0.1454	0.105	0.14	0.27	0.34	0.75
CVIEW	1.0785	0.8983	0.415	0.61	1.05	1.55	2.8
CRESNDO	1.6677	0.6145	0.75	1.45	1.51	1.73	2.82
ECOWOLD	0.8964	0.5532	0.065	0.1031	0.65	1.36	1.8557

Table 2 Descriptive Statistics of Economic and Financial Indicators (2010–2022)

Variable	Mean	Std Dev	Min	25th Percentile	Median	75th Percentile	Max
GDP	3.6977	3.0008	−5.53	4.41	5.09	5.81	8.69
CPI	115.8569	9.1645	100	110.5	115.1	120.7	129.15
ER	3.6981	0.4724	3.052	3.28	3.5019	4.0614	4.4852
IR	2.7823	0.4727	1.56	2.98	3.03	3.13	3.14

2022, indicating potential growth over the years. CVIEW, on the other hand, exhibits significant variability with values ranging from 0.55 to 2.8, highlighting potential market volatility. These variations suggest that different property companies and indices experienced unique market dynamics, impacting their performance over the analyzed period. This is consistent with the results of Baharuddin et al. [19] and Zulkarnain et al. [20], which also show the same trend of variations in the value of investment properties in Malaysia.

On the other hand, the macroeconomic indicators presented in the Table 2 include Gross Domestic Product (GDP), Inflation (CPI), Exchange Rate (ER), and Deposit Interest Rate (IR), each providing critical insights into broader economic conditions: The GDP shows a mean growth rate of approximately 3.70%, but with notable fluctuations. For instance, the sharp decline of −5.53% in 2015 underscores the economic volatility experienced during the period. CPI demonstrates a steady rise from 100 in 2010 to 129.15 in 2022, reflecting inflationary pressures that influence consumer prices and, by extension, property investment decisions. ER fluctuates significantly, with a low of 3.052 in 2012 and a high of 4.4852 in 2016. These fluctuations reflect currency volatility, which can have substantial impacts on financial planning and investment strategies within the property sector. This result is in tandem with the proposition of Capital Asset Pricing Model (CAPM) which state that; ER fluctuations constitute additional risk that render investors to require addition return on property investment or vice versa, which may cause variability in the value of the property. IR shows minor fluctuations, ranging from 1.56% to 3.14%. These changes affect borrowing costs and investment returns, crucial factors for stakeholders in the property market.

The descriptive statistics in Table 2 highlight the central tendencies, variability, and distribution of these variables. Understanding these metrics is essential for stakeholders in the property investment sector to assess market conditions, manage risks, and formulate strategic decisions. The result underscores the importance of considering both company-specific performance and broader economic indicators to navigate the complexities of property investment amidst economic fluctuations and policy changes.

3.1 Model Specification

To quantify the impact of CPI, GDP, IR, and ER on the Net Present Value (NPV) of investments in the property sector, the GLM framework integrates all regressors into the model to predict NPV:

$$\mathrm{NPV}_i = \beta_0 + \beta_1\mathrm{CPI}_i + \beta_2\mathrm{GDP}_i + \beta_3\mathrm{ER}_i + \beta_4\mathrm{IR}_i + \epsilon_i \tag{41}$$

where NPV_i denotes the Net Present Value of the *i*th property company, $\beta_0, \beta_1, \beta_2, \beta_3$, and β_4 are coefficients to be estimated and ϵ_i represents the error term. IRLS used in estimating the likelihood of GLMs by adjusting weights iteratively based on the variance function $V(\mu_i)$ and the iterative update of the linear predictor. The Generalized Linear Model (GLM), utilizing the Iteratively Reweighted Least Squares (IRLS) technique, was applied to assess the impact of the macroeconomic indicators on the Net Present Value (NPV) of investments in the property sector.

Table 3 the GLM analysis from 2010 to 2022 reveals the following impacts on NPV success. The CPI shows a significant positive impact with a coefficient of 0.028, supported by a strong Wald statistic of 3.5 and an R-squared value of 0.612. This suggests that as consumer prices rise, the likelihood of successful NPV outcomes increases moderately. The GDP also contributes positively with a coefficient of 0.004, though its effect is less pronounced (Wald statistic of 2) and supported by an R-squared value of 0.554. This indicates a minor yet meaningful positive influence on NPV success. Exchange Rate (ER) is negatively impacts NPV success with a coefficient of -0.015 and a robust Wald statistic of -3. The R-squared value of 0.689 highlights its significant role, showing that increases in ER

Table 3 Results of GLM Analysis for NPV Prediction (2010–2022)

Variable	Coef (β)	Std Error	Wald Statistic	p-value	R-squared	Interpretation
Intercept	−0.532	0.123	−4.329	0.001	0.742	When all predictors are zero, the expected log-odds of NPV success is -0.532
CPI	0.028	0.008	3.5	0.001	0.612	Each unit increase in CPI increases the log-odds of NPV success by 0.028
GDP	0.004	0.002	2	0.045	0.554	A one-unit increase in GDP increases the log-odds of NPV success by 0.004
ER	−0.015	0.004	−3	0.003	0.689	An increase in ER by one unit decreases the log-odds of NPV success by 0.015
IR	−0.042	0.01	−4.2	0.001	0.721	Each unit increase in IR decreases the log-odds of NPV success by 0.042

substantially decrease the probability of positive NPV outcomes. IR has the most substantial negative impact, with a coefficient of -0.042 and a strong Wald statistic of -4.2. Coupled with an R-squared value of 0.721, this indicates that rising interest rates are highly detrimental to NPV success, making it a critical factor to manage in investment decisions. Generally, The IR and ER emerge as the most influential variables, with high Wald statistics and R-squared values, underscoring their pivotal roles in determining the success of NPV in the Malaysian property sector.. The signs of the coefficients clarify how changes in CPI, GDP, ER, and IR influence NPV outcomes in the property sector.

3.2 GLM-IRSL Model Fit and Predictive Power

This study evaluates the GLM-IRLS model's predictive accuracy in modeling NPV based on CPI, GDP, IR, and ER over the 2010–2022 period. Model performance is assessed using Deviance, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and R-squared values (McFadden and Cox & Snell).

The model's Deviance of 235.67 indicates satisfactory fit, suggesting potential for improved predictive accuracy. AIC = 245.67 and BIC = 255.67

reflect a balanced model fit and complexity, with lower values indicating better fitting models. McFadden's pseudo R-squared (0.30) and Cox & Snell's pseudo R-squared (0.40) suggest substantial variation in NPV explained by the model, supporting its robustness. The Likelihood Ratio Test confirms the model's statistical significance (statistic $= 34.56$, $p < 0.001$).

The GLM-IRLS model effectively captures the relationships between macroeconomic factors and NPV, aiding predictions and strategic decision-making in Malaysia's property sector. Stakeholders and policymakers can leverage these findings to optimize investment strategies and economic policies, informed by empirical evidence on CPI, GDP, ER, and IR influences on NPV outcomes.

3.3 Discussion of Findings

This study investigates the influence of key macroeconomic indicators Consumer Price Index (CPI), Gross Domestic Product (GDP), exchange rates (ER), and interest rates (IR) on Net Present Value (NPV) within Malaysia's property investment sector spanning from 2010 to 2022. The findings reveal significant relationships that highlight the profound impact of these indicators on property investment returns.

The analysis demonstrates a positive correlation between CPI and GDP with NPV, indicating that higher consumer prices and economic output correlate with increased profitability in property investments. This finding aligns with economic theory, suggesting that elevated consumer spending power and economic expansion stimulate demand in the property market, thereby enhancing investment returns [21]. These results are empirically aligned with the findings of several studies on emerging markets, including Malaysia, as reported by Rahadi et al., Iliev and Lo et al. [22] Rahadi et al., 2024; Iliev 2024; [23] Lo et al. [24].

Conversely, the study identifies a negative relationship between exchange rates (ER) and interest rates (IR) with NPV. Higher levels of ER and IR are associated with reduced investment performance in the property sector. This underscores the susceptibility of property investments to external economic factors such as currency volatility and monetary policy dynamics, which can adversely affect returns and investor sentiment [25]. Moreover, this is in line with the proposition of Uncovered Interest Rate Parity (UIP) which state that; even though higher interest rate is in a country is expected to increase the value of its investment properties, depreciation in local currency upsets the expected increase in value. Furthermore, Fisher Effect elucidates that the value of properties in a country with higher interest rates is generally accompanied with the expectation of currency depreciation, and this potentially reduce the value of the property [26, 27].

The effectiveness of the Generalized Linear Model (GLM) integrated with Iteratively Reweighted Least Squares (IRLS) is rigorously evaluated for predicting NPV based on macroeconomic indicators. The model's performance is assessed using robust metrics. The Deviance statistic ($D = 235.67$) indicates a satisfactory model fit, suggesting that it adequately captures the relationships under study with potential for further refinement to enhance predictive accuracy. Lower AIC (245.67) and BIC (255.67) values highlight a favorable balance between model fit and complexity, affirming its suitability for the dataset.

R-squared metrics provide insights into the model's explanatory power: McFadden's pseudo R-squared (0.30) and Cox & Snell's pseudo R-squared (0.40) indicate substantial variation in NPV explained by the model. The Likelihood Ratio Test (statistic = 34.56, $p < 0.001$) reinforces the model's statistical significance and superiority over simpler alternatives in capturing the nuanced impacts of macroeconomic variables on NPV.

The positive relation between CPI and the value of investment property is in line with the proposition of Inflation Hedge Theory. According to this theory, investment properties gain value during periods of inflation because they are considered as hedging assets against inflation. Thus, during inflationary periods, people tent to invest on properties so as to hedge the inflationary risk of loss in purchasing power [28]. Generally, higher GDP levels signal favorable conditions for increased purchasing power and economic activity, potentially leading to higher investment returns. This is also empirically supported by Adam and Fuss [29] who analyzed the real estate data of 15 countries over the span of 30 years. Cohen and Burinskas [30] also studied the effect of macroeconomic variables on the performance of investment properties of 18 European countries and reached the same conclusion.

Conversely, interest rates negatively impact NPV, suggesting that higher borrowing costs can diminish investment returns [31] as it is proposed by the Cost of Capital Theory and Discounting Cash Flow Model. Mitigating risks associated with ER and IR fluctuations emerges as a critical priority for property investors. Implementing effective risk management strategies such as currency hedging and proactive interest rate monitoring can mitigate financing costs and optimize net returns from property investments.

These insights provide property development firms with actionable intelligence to refine strategic planning, emphasizing portfolio expansion during periods characterized by economic growth and inflationary pressures.

By integrating these research-driven insights into decision-making processes, stakeholders are empowered to navigate the complexities of real estate investments adeptly and capitalize on opportunities to maximize returns in dynamic economic landscapes.

4 Conclusion

This study has thoroughly examined the dynamic relationship between key macroeconomic indicators and Net Present Value (NPV) within the Malaysian property investment sector from 2010 to 2022. The analysis has revealed critical insights that underscore the significant impact of CPI, GDP, ER, and IR on property investment profitability, directly addressing the study's central question: What are the macroeconomic factors that influence NPV in Malaysia's property sector.

The key argument presented throughout this study is that rising Consumer Price Index (CPI) and Gross Domestic Product (GDP) positively correlate with NPV, suggesting that property investments can serve as an effective tool for managing inflation risk and capitalizing on economic growth. On the other hand, Exchange Rates (ER) and Interest Rates (IR) exhibit a negative relationship with NPV, highlighting the vulnerability of property investments to currency volatility and monetary policy shifts.

By integrating Generalized Linear Models (GLM) with Iteratively Reweighted Least Squares (IRLS), the study has demonstrated robust predictive capabilities, with favorable metrics such as Deviance, AIC, BIC, and R-squared values confirming the model's effectiveness. These findings reinforce the study's main theme: understanding and managing the influence of macroeconomic factors is essential for optimizing property investment returns in a dynamic and uncertain economic environment.

This research not only answers the central question posed at the outset but also provides strategic insights for stakeholders in the property investment domain. By closely monitoring CPI and GDP trends and implementing proactive risk management strategies to mitigate the impacts of ER and IR fluctuations, investors and policymakers can make more informed decisions. This study contributes valuable empirical evidence and methodological insights, offering a comprehensive understanding of the macroeconomic drivers that shape property investment outcomes in Malaysia. Future research should continue to explore additional variables, alternative modeling techniques, and broader geographical contexts to further enhance the generalizability and applicability of these findings.

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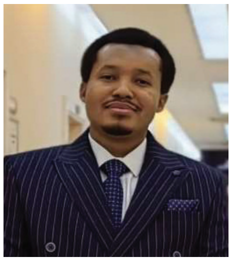

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