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Dividend Yield Modelling and Forecasting under the Wilkie Investment Model with Inflation Effects: Evidence from Malaysia

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Abstract

This study uses the Wilkie Investment Model in the context of the Malaysian stock exchange, incorporating inflation as a significant factor in explaining investment behavior in line with local economic conditions. Although the Wilkie model is broadly utilised in actuarial science and has been assessed in many developed countries, its use in emerging markets such as Malaysia is still limited. Based on historical data from Malaysia, both the dividend yield and inflation series were revealed to be stationary using the Augmented Dickey-Fuller (ADF) test. Therefore, the series is applicable for time series analysis. The study used Malaysian data to estimate the Wilkie model and compare it with the original model's parameters used in the United Kingdom market. The study employs the Mean Absolute Percentage Error (MAPE) to evaluate the model's forecasting accuracy and the Impulse Response Function (IRF) to assess the interaction between inflation and the dividend yield. The Malaysia-calibrated model surpassed the Wilkie parameters in predictive power, achieving an MAPE of 16%, a satisfactory level of predictive accuracy. The IRF results demonstrated that, in the short term, inflation shocks possess a negative impact on dividend yields, implying that inflation dampens dividend yields. Overall, this study presents the need to localize model parameters and the impact of inflation on dividend yields in emerging economies.

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1.0 Introduction

Dividend yield is the ratio of a firm's annual dividend payments to its market price, expressed as a percentage. It serves as a key indicator of an investment's income-generating capacity (Ruhani & Mat Junoh, 2023) and evaluates the return investors receive from dividends. In financial markets, the dividend yield is particularly significant for those prioritizing regular returns over capital gains, as stable or rising yields signal a company's financial health and viable business structure. In contrast, declining yields may indicate potential risks (Gwilym et al., 2000). Under economic uncertainty, dividend-paying stocks tend to appeal to investors as a source of stability and income protection (Hasan et al., 2023).

One of the most recognized models in the actuarial and financial fields is the Wilkie Investment Model, established by A.D. Wilkie in 1986. This stochastic, Autoregressive (AR) model is designed to forecast long-term economic and financial variables, including the Retail Price Index (RPI), dividend index, dividend yields, and interest rates. This model captures the interrelation of these variables across economic cycles (Wilkie, 1986). Subsequently, Wilkie updated the model in 1995 because refinement was required to improve its practical use. This updated version addressed limitations and introduced improvements in parameter estimation, correlation structures, and dependencies among financial variables (Wilkie, 1995).

There is an outstanding gap in the literature with regard to the robust modelling of dividend yields suitable for emerging markets such as Malaysia. Although the Wilkie Investment Model has been proven valid in developed markets, particularly using UK data, there is limited research on its application in emerging markets, which exhibit distinct economic structures, inflation dynamics, and market structures (Wilkie, 1995). Consequently, the applicability of the model's assumptions and sensitivities may not be directly applied to the Malaysian economy without empirical validation. Although the Wilkie framework accounts for both dividend yields and inflation, its reliance on the Consumer Price Index (CPI) as a measure of inflation may inadequately capture real-world inflation shocks. This, in turn, leads to biased projections of dividend yields (Huber

1995). Therefore, this study aims to assess the accuracy and applicability of the Wilkie Investment Model after recalibrating it for the Malaysian economy.

The objectives of this study are to estimate the parameters of the Wilkie Investment Model using Malaysian data and to generate future dividend yields by applying the Wilkie dividend yield model and Monte Carlo simulation. Additionally, this study seeks to evaluate the accuracy of the Wilkie dividend yield model by comparing forecasted yields with historical dividend yields in Malaysia. It also examines the impact of inflation on dividend yields.

2.0 Literature Review

This section reviews past literature on the general view of dividend yields, the structure of the Wilkie Investment Model, and the interdependencies between variables. The dynamic relationship between inflation and dividend yield, the application of forecasting in financial research, and the importance of Monte Carlo simulations are also discussed in detail.

2.1 The Wilkie Stochastic Investment Model

The Wilkie Investment Model was developed by A.D. Wilkie in 1986 for actuarial purposes. This model is primarily used to identify the factors affecting an investment's returns. The foundation for the Wilkie model structure was established based on the ideas of Box and Jenkins developed in 1976. The main components in the Wilkie model are price inflation, share dividend yield, dividend index, and consols yield (Ishak, 2015). Each component might influence other components, starting with the retail prices index model, which in turn influenced the share dividend yield, dividend index, and consols yield. Furthermore, the share dividend index and consols yield were determined using the share dividend yield model. The directions of the components are expressed in a cascade diagram, as shown in Figure 1.

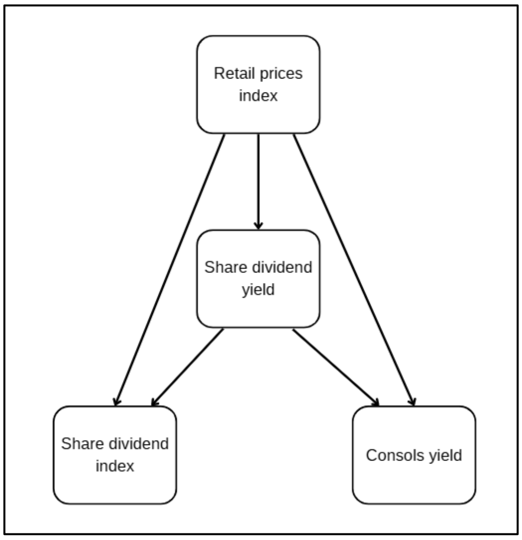

Figure 1: The Wilkie Model (Wilkie, 1986)

In 1995, A.D. Wilkie updated the Wilkie model by introducing more economic variables that impacted the return on investment. The new variables included in the Wilkie model (1995) were the wage index, short-term interest rates, and share prices. The updated Wilkie model also includes a cascade diagram to demonstrate the direction of influence for each variable. The structure of the Wilkie model 1995 is shown in Figure 2.

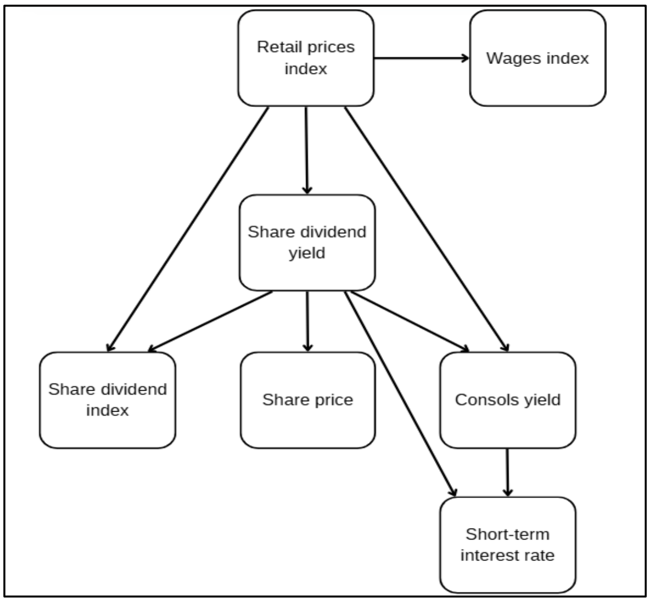

Figure 2: The Wilkie Model (Wilkie, 1986)

Based on Figure 2, the retail price index directly influences the wage index and other assets, including share dividend yields, the dividend index, and consols yield. The short-term interest rate model was directly dependent on console yield. Meanwhile, the retail price index was chosen as the primary determinant because of its ability to estimate real asset returns accurately (Ishak, 2015). Building on the structural models in Figures 1 and 2, past research has revealed that the Wilkie model provides an integrated framework for understanding the joint behavior of inflation and equity returns through its interrelated price index and dividend yield components. Although derived for the UK market, Wilkie (1995) extended its framework to data from other countries, demonstrating that its component-based structure can be adapted to different macro-financial environments. However, empirical evidence on its applicability to emerging markets such as Malaysia remains limited, as the dynamics of inflation, dividend yields, and market structures may differ significantly from those in developed economies. Correspondingly, this study aims to extend this research gap by using the Wilkie model and assessing its applicability and performance in Malaysia.

2.2 Dynamic Relationship Between Inflation and Dividend Yield

Inflation is positively correlated with the equity dividend yield. In the context of a theoretical framework, dividend yield should be positively correlated with predicted inflation, negatively correlated with expected cash flow growth, and positively correlated with equity risk premium and interest rate. One study indicates that most of the positive covariance between inflation and dividend yield is driven by the synchronized movement of inflation and equity risk premium. This suggests higher returns or discount rates (Bekaert & Engstrom, 2009). However, inflation also exhibits a significant negative correlation with dividend yield, since surging interest rates reduce distributable retained earnings (Agustin, 2019). This is the opposite of what is observed in developed markets, where a countercyclical policy tends to establish a positive relationship between dividends and inflation. In developing markets, high inflation reduces payout potential by driving an inverse relationship between dividends and inflation (Khan et al., 2013).

The empirical analysis of inflation and dividend yields suggests that the interaction between the variables is highly dynamic, as equities do not provide consistent protection against inflation fluctuations, particularly in the short term. Dividend yield may rise during periods of inflation if stock prices decline more rapidly than dividends (Pilotte, 2003; Khan et al., 2013). Subsequent literature suggests that either weak or unstable correlations exist between inflation and dividend yields. Nevertheless, stronger links were observed over longer periods. The dividend yield is informative about future inflation across markets, suggesting that valuation ratios can incorporate information about future macroeconomic conditions. However, this relationship is inconsistent, as it relies on the sample period, the current monetary regime, and whether the measured expected or unexpected inflation is properly specified (Engsted & Pedersen, 2016). Following this, evidence across countries demonstrates that the behavior of emerging markets differs from that of developed markets in terms of inflation persistence, dividend policy, and market efficiency (Osman, 2024).

To capture the dynamic relationships illustrated above, Vector Autoregression (VAR) models have been widely used within the literature. VAR models permit the inclusion of inflation and dividend yields as interdependent variables. This method allows researchers to capture feedback effects and lead-lag relationships between inflation and dividend yield (Engsted & Pedersen, 2016). By explicitly modelling inflation and dividend yields in the Wilkie framework and the VAR model, this study adds on to the literature by investigating whether the relationship between inflation and dividend yields in Malaysia is consistent with that observed in developed or emerging markets. In addition, it assesses the stability of this dynamic relationship over time.

2.3 Forecasting using a Stochastic Model

Economic and financial forecasting increasingly relies on stochastic modelling to capture economic uncertainty, randomness, and the dynamic characteristics embedded in time-series data. In contrast to deterministic models, stochastic models explicitly incorporate probabilistic structures that allow forecasted outcomes to reflect the uncertainty inherent in a time series (Bergeron, 2024). Stochastic forecasting models have been developed using time series models such as AR, Moving Average (MA), and Autoregressive Moving Average (ARMA) processes, in which the current values are based on past observations and random shocks (Box & Jenkins, 1976).

The Wilkie Investment Model refers to a stochastic asset model that jointly forecasts inflation, dividend yields, equity returns, and interest rates over the long term through a system of interlinked processes. A key feature of the model is its reliance on first-order- AR(1) processes, which allow for persistence and mean-reverting properties in time series, while enabling shocks to be transmitted between variables (Wilkie, 1986). This combination of stochastic simulation and interlinked AR(1) processes makes the Wilkie model particularly appropriate for long-term- forecasting in the context of this study.

2.4 The Importance of Monte Carlo Simulation

Simulation is an essential element of stochastic modelling as it enables practitioners to extend beyond point forecasts by repeatedly simulating random innovations from predicted probability distributions. Notably, the Monte Carlo simulation produces multiple possible pathways for key variables, allowing speculation on both expected behavior and uncertainty over time. This approach allows stochastic models to convey the complex dynamics, volatility, and accumulating uncertainty that emerge naturally over prolonged horizon forecasts. Hence, simulation-based forecasting provides detailed information, including confidence quantiles, intervals, and tail outcomes, which are essential for assessing risk exposure and variability (Glasserman, 2004; Thadani, 2021).

The flexibility of modelling potential future outcomes makes the Monte Carlo simulation technique especially useful in environments characterized by uncertainty and stochastic processes. For instance, one study describes the use of Monte Carlo simulations for financial option pricing. It covers random sampling from uniform and Gaussian distributions, variance-reduction techniques such as importance sampling and paired sampling, and sequences that are uniformly distributed to improve the convergence rate of the standard error of the mean (Lapeyre & Jourdain, 2021). The integration of simulation techniques into stochastic models improves forecast reliability by accounting for uncertainty and risk, which are crucial aspects of financial and actuarial forecasting.

Previous research extensively used Monte Carlo simulations to develop stochastic scenarios from economic models, facilitating the evaluation of uncertainties in future outcomes rather than relying on a single path. This approach is particularly useful in the Wilkie model, in which multiple interrelated variables simultaneously change over time. Therefore, this study employs a Monte Carlo simulation to examine the distribution of future inflation and dividend yields in Malaysia. This approach is crucial for a more comprehensive evaluation of uncertain outcomes, which are vital for long-term financial decision-making.

3.0 Methodology

This study used secondary data from monthly observations from 2015 to 2024. This timeframe enabled a comprehensive analysis of 118 months, from March 2015 to December 2024. The dataset comprises dividend yield data from the FTSE Bursa Malaysia KLCI (FBMKLCI) and CPI data sourced from the Department of Statistics Malaysia (DOSM) as a proxy for the inflation rate in Malaysia.

3.1 Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test refers to a critical test in time series analysis that determines if a time series is stationary or non-stationary by evaluating the presence of a unit root, which indicates non-stationarity. The hypothesis of the ADF test is as follows:

H_0 : The series has a unit root, $\gamma = 0$.

H_1 : The series does not have a unit root, $\gamma < 0$.

To prove that the series is stationary, the null hypothesis must be rejected by comparing the test statistic to the critical value or by having a p-value lower than the 5% significance level.

3.2 Wilkie Investment Model

The application of the Wilkie Investment Model in this study was to test its accuracy in simulating future dividend yield behavior. Although dividend yield is the focus of this study, including the RPI is necessary since the Wilkie model's cascade structure assumes that the dividend yield is influenced by inflation. Consistent with the original Wilkie framework, the AR(1) process has been used to model the behavior of dividend yield and inflation, considering the persistence and mean-reverting properties of economic variables, as commonly observed in economic time series. The simplicity of the AR(1) process enables the model to adequately describe the interaction between inflation and dividend yield.

3.2.1 Retail Price Index Model

The RPI model assumes that the logarithmic change in the price index follows an AR(1) process with a constant term and random error for a realistic simulation of inflation dynamics. This model uses (1) to first determine the inflation rate over the year.

$$I(t) = \ln Q(t) - \ln Q(t-1), \qquad (1)$$

in which $Q(t)$ refers to the value of the RPI at time t. The AR(1) model of the RPI is given below:

$$I(t) = QMU + QA.(I(t-1) - QMU) + QE(t), \qquad (2)$$

$$QE(t) = QSD.QZ(t),$$

$$QZ(t) \sim iidN(0,1).$$

Based on (2), QMU is the long-term mean rate of inflation, QA represents the AR coefficient, $QE(t)$ denotes a random innovation term at time t, and QSD denotes the standard deviation of the random innovation. Meanwhile, $QZ(t)$ resembles a standard normal random variable with mean zero and one standard deviation that is independently distributed. Originally, the RPI model was mainly used for UK data, where the RPI is used as a measure of inflation and serves as the basis for modelling price-level changes within the Wilkie framework. However, Malaysia commonly uses the CPI rather than the RPI to measure inflation. Therefore, the RPI component in the model is replaced with CPI to maintain the model's relevance and accuracy.

3.2.2 Dividend Yield Model

The dividend yield model within the Wilkie Investment Model is designed to represent the stochastic behavior of dividend yields over time. The model is specified as follows:

$$\ln Y(t) = \ln YMU + YW.I(t) + YN(t), \tag{3}$$

$$YN(t) = YA.YN(t-1) + YE(t),$$

$$YE(t) = YSD.YZ(t),$$

$$YZ(t) \sim iidN(0,1),$$

where YMU is the mean level of dividend yield, YW is the sensitivity of dividend yield to inflation, and $YN(t)$ is the deviation term for dividend yield at time t. YA refers to the AR coefficient, $YE(t)$ denotes the random innovation term at time t, and YSD is the standard deviation of random innovation.

3.3 Parameter Estimation

The parameters of the RPI and dividend yield models were estimated using Ordinary Least Squares (OLS) to ensure that the model's parameters were adapted to the Malaysian context, as the original parameters of both models were based on UK data. Therefore, this step was required to determine the applicability of the model to Malaysian data. Before estimation, the dataset was divided into two sets: a training set and a test set. The training data covered the period from March 2015 to January 2022, approximately 83 months, for parameter estimation. From February 2022 to December 2024, 35 datasets were used as test data to forecast and simulate dividend yields for model evaluation. This partitioning step was crucial as it prevented overfitting and ensured that the model generalizes well to the dataset.

3.4 Monte Carlo Simulation

The forecasting process was conducted using the actual historical inflation rate of the testing dataset (February 2022 to December 2024), while $YN(t)$ was simulated for 1,000 paths using Monte Carlo. The model applied was based on the Wilkie framework, as illustrated below:

$$\ln \widehat{Y(t)} = \ln YMU + YW.I(t) + \widehat{YN(t)}, \tag{4}$$

in which $I(t)$ denotes the actual inflation from testing data. Random shocks for the stochastic component, $\widehat{YN(t)}$ were drawn from a Gaussian distribution:

$$\varepsilon_t \sim N(0, \hat{\sigma}_\varepsilon^2). \tag{5}$$

Each of these simulated paths combines actual inflation data with random shocks that would affect the dividend yield. The average of 1,000 simulated paths was then taken as the forecasted dividend yield for each month. To implement the Monte Carlo simulation, a simplified version of the Wilkie framework was used, given the objectives of this study. It must be noted that the Wilkie Investment Model, as originally proposed, constituted a fully stochastic system of interrelated economic variables. However, this study uses a simplified version of the model, treating inflation as an exogenous input during the forecasting period. It should be noted that although the model did not account for feedback effects among the variables, the simplified version used here provided a tractable forecasting framework consistent with the study's objectives.

3.5 Model Evaluation

This research evaluated the accuracy of the dividend yield model using the Mean Absolute Percentage Error (MAPE). The forecasted value of the dividend yield was referred to as $\ln\widehat{Y(t)}$, while the actual value was $\ln Y(t)$. The observation period was from February 2022 to December 2024 at monthly intervals. The MAPE was calculated using the following formula (Chicco et al., 2021):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{\ln Y(t)-\ln\widehat{Y(t)}}{\ln Y(t)}\right|. \tag{6}$$

This study employed the indicator values in Table 1 to assess the accuracy of the dividend yield model.

Table 1: Scale of Judgement MAPE (Lewis, 1982)

MAPE Value	Prediction Accuracy
$\text{MAPE} \leq 10\%$	High
$10\% < \text{MAPE} \leq 20\%$	Good
$20\% < \text{MAPE} \leq 50\%$	Reasonable
$\text{MAPE} > 50\%$	Low

3.6 Impulse Response Function (IRF) Analysis

To examine the dynamic correlation between shocks to inflation and the dividend yield, the Impulse Response Function (IRF) was used to demonstrate the dividend yield's response to an inflation-rate shock across 118 datasets. Estimating the IRF required an optimal lag length for the VAR model to avoid overfitting while still capturing the dynamic relationship between inflation and dividend yield. Following this step, the appropriate lag length is estimated based on the chosen VAR model. Subsequently, the IRF is computed from the VAR specification to analyze the dynamic response of the dividend yield to inflation shocks.

4.0 Results and Discussion

This section reports the empirical findings of this study. It begins with Descriptive Statistics (4.1) to establish the dataset's fundamental properties, followed by the ADF Test (4.2) to assess the stationarity of the variables. After these preliminary diagnostics, Parameter Estimation (4.3) is performed to determine the model's coefficients, which inform the subsequent Monte Carlo Simulation (4.4) used to forecast future trends under various scenarios. The analysis concludes with an IRF Analysis (4.5), which evaluates the temporal responses of the variables to unexpected external shocks, thereby providing a comprehensive understanding of their dynamic interrelationships.

4.1 Descriptive Statistics

Table 2: Descriptive Statistics Summary

Statistics	$\boldsymbol{Y(t)}$	$\boldsymbol{I(t)}$
Mean	0.02963	0.00164
Median	0.02228	0.00163
Maximum	0.09506	0.01262
Minimum	0.00068	-0.02767
Standard Deviation	0.02243	0.00466
Skewness	0.95982	-2.19488
Kurtosis	0.15069	13.82007
Observations	118	118

Based on Table 2, the dividend yield had a mean of 2.96% and a median of 2.26%, with a slight right skew due to some high-yield months. The minimum dividend yield was approximately 0.07%, and the maximum was approximately 9.51%. Although the values were small, notable fluctuations were observed. A standard deviation of 2.23% reflected substantial variation around the mean. The skewness measure of 0.96, with an excess kurtosis of 0.15, reflected slightly larger tails than normal tails. The dividend yield series exhibited moderate variation, mild asymmetry, and a near-normal tail, which are characteristics common in financial data and are occasionally observed.

The mean inflation rate was 0.16%, with the median slightly different from the mean, indicating a value of zero as the central tendency. The minimum inflation rate was approximately -2.77%, while the maximum was approximately 1.26%. This finding suggests the existence of negative shocks as well as smaller positive influences. Despite the standard deviation being only 0.47%, the coefficient of variation was extremely high because the mean was near zero, suggesting high volatility. Meanwhile, the distribution was highly left-skewed at -2.12, and depicted an extremely high leptokurtosis of approximately 13.09, indicating very heavy tails and frequent outliers. These characteristics reveal that inflation is relatively volatile and asymmetric.

4.2 Augmented Dickey-Fuller (ADF) Test

Table 3: The Result of the ADF Test

Variables	Critical value	Test statistic
$\ln Y(t)$	-3.4487	-7.7925
$I(t)$	-3.4484	-8.3266

Based on Table 3, the test statistic of $\ln Y(t)$ was compared to the critical value for 5% significance level of -3.4487. Because the test statistic for -7.7925 was below the critical value, the null hypothesis of the unit root was rejected. This result suggested that the series of $\ln Y(t)$ was stationary. Moving on to $I(t)$, the test statistic was -8.3266, which was smaller compared to the 5% critical value of -3.4484. This finding suggests that the null hypothesis of $I(t)$ was rejected; hence, the series was stationary.

4.3 Parameter Estimation

Table 4: The Parameter Estimation of $I(t)$

$I(t)$	Parameter	Parameter (Sahin et al., 2008)
QMU	0.001581	0.0446
QA	0.256073	0.5794
QSD	0.005288	0.0396

Table 4 presents the parameter estimates for the RPI model estimated by OLS. Based on the parameter estimation results for the RPI model, the most significant parameter was QA, with a coefficient magnitude of approximately 0.256. In contrast, the coefficients of QMU and QSD are relatively small at 0.0016 and 0.0053, respectively. Notably, this parameter estimation also underscored the significance of the QA parameter, as the model multiplied by the lagged CPI term, indicating the prominence of the persistence effect. Compared with a previous study that used RPI, the coefficient values differed markedly. For example, QA in this study was approximately half the value reported in a previous study, and QMU and QSD were considerably smaller. The major reason for this variation in findings was differences in the choice of inflation variable: past studies used RPI, while this study used CPI. The differences between the RPI and CPI were in their coverage and weightage. The CPI highlighted households' consumption habits, while the RPI included additional elements, such as housing and mortgage interest costs, which likely explains the observed differences in parameter estimates.

Table 5: Diagnostic Test of Residual for $\boldsymbol{I(t)}$

Diagnostic Test	Probability
Breusch-Pagan-Godfrey	0.0010
Ljung-Box (at lag 1)	0.4300
Jarque-Bera	0.0001

Diagnostic tests are always indicative of significant features in the residuals of the model. Note that the Breusch-Pagan-Godfrey test strongly rejects the null hypothesis of homoscedasticity, with p-values well below 0.001 across all F-statistics. This result indicates heteroscedasticity, where the variance of the residuals is not constant. To address heteroskedasticity in regression residuals, heteroskedasticity-consistent standard errors, commonly referred to as Huber-White, are employed (Huber, 1967; White, 1980). Although heteroskedasticity did not bias the OLS coefficient estimates, it made conventional standard errors inconsistent. The Huber-White approach adjusts the variance–covariance matrix of the estimated coefficients to account for this non-constant error variance without assuming its functional form. This method provides asymptotically valid inference under general conditions and is widely recommended when the assumption of homoscedasticity is violated (Astivia & Zumbo, 2019). For the autocorrelation test, the Ljung-Box Q-statistics indicate no evidence of autocorrelation, as the p-values were greater than 0.05, across all lags.

Table 6: The Parameter Estimation of $\ln Y(t)$

$\ln Y(t)$	Parameter	Parameter (Sahin et al., 2008)
YMU	0.0191	0.0364
YW	-26.8550	1.6473
YA	0.2563	0.6354
YSD	0.9651	0.1529

Table 6 presents the parameter estimates for the dividend yield model estimated by OLS. The estimated parameters provided important insights into the dynamics of dividend behavior. The intercept, ln YMU, was estimated to be 0.0191, representing the mean level of the dividend yield in logarithmic form. The coefficient on the inflation sensitivity, YW, was highly negative (-26.8550), corresponding to the inverse relationship between inflation and dividend yield. The results reveal that as inflation rises, dividend yield falls, which is associated with lower real cash flow and lower dividend attractiveness to investors (Pilotte, 2003). Inflation also increases uncertainty about future earnings, consistent with dividend-smoothing behavior, in which firms tend to retain profits rather than pay higher dividends (Bergeron, 2024). Furthermore, inflation increases operating and financing expenses, compressing profit margins and reducing the cash available for dividend distributions, especially in emerging markets (Osman et al., 2024). These findings are consistent with the theoretical and empirical literature, which confirms that inflationary pressure negatively affects firms' dividend-paying capacity.

The AR coefficient, YA (0.2563), represented moderate persistence in dividend yield deviations. This result implies that shocks to dividend yield do not permanently alter its level, yet gradually diminish over time, reflecting a mean-reverting process. The volatility parameter, YS, coefficient was relatively high compared to previous studies, with 0.9651. This suggests that dividend yields in the sample period exhibit greater variability. In essence, this finding was plausible given the inclusion of economic shocks such as the COVID-19 pandemic and subsequent inflationary pressures.

A comparison with a previous study revealed substantial differences in parameter estimation. These differences could be attributed to the choice of inflation index used in this study, variations in the sample periods, and economic conditions. The weights and coverage of the RPI and CPI differ, leading to differences in their values and affecting the estimated sensitivity of dividend yields to inflation. Furthermore, including recent macroeconomic shocks in the sample is likely to increase volatility in the relationship between inflation and dividend yields.

Table 7: Diagnostic Test of Residual for $\ln \boldsymbol{Y}(\boldsymbol{t})$

Diagnostic Test	Probability
Breusch-Pagan-Godfrey	0.8936
Ljung-Box (at lag 1)	0.0180
Jarque-Bera	0.0143

The diagnostic tests provided additional information to improve the adequacy of the model. The Breusch-Pagan-Godfrey test failed to reject the null hypothesis of homoskedasticity since the residual variance was constant, as indicated by the p-value (0.8936) exceeding 0.05. In contrast, the Ljung-Box test revealed significant autocorrelation at multiple lags, with p-values below 0.05 for lags 1-6, consistent with the AR structure of the deviation term. Hence, the conventional OLS standard errors were inconsistent, even though the parameter estimates were unbiased under classical assumptions. To have a valid inference for time-series regressions where residuals were reported to be autocorrelated, Heteroskedasticity and Autocorrelation Consistent (HAC) standard errors were used (Newey & West, 1987). This adjustment was vital in the time series, where autocorrelation was common, and ignoring it can lead to size distortions and unreliable hypothesis testing (Baillie et al., 2024). Moreover, the application of HAC resulted in a smaller standard error. As a result, the HAC-based inference yielded a more precise estimation, thereby increasing the statistical significance of some coefficients.

4.4 Monte Carlo Simulation for Forecasting

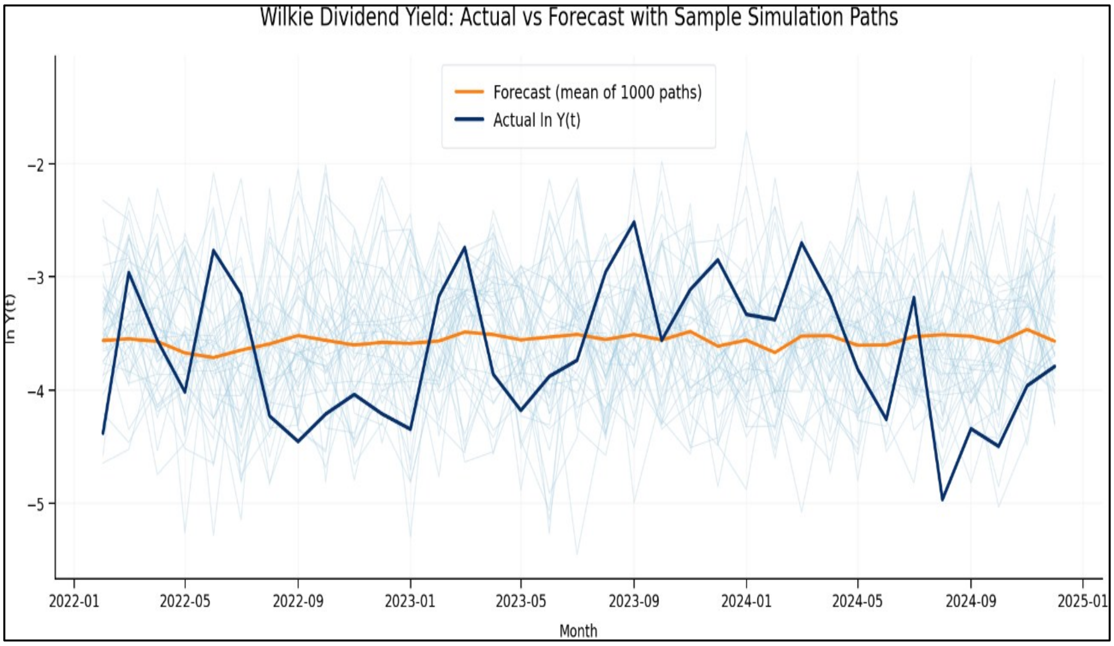

Figure 3: Actual and Forecast of ln $\boldsymbol{Y(t)}$ Graph

Figure 3 presents Monte Carlo simulation paths of $ln\, Y(t)$ over time. The horizontal axis, demonstrated in months, ranges from January 2022 to January 2025, while the vertical axis indicates $ln\, Y(t)$ values from -5 to -2. There are three main elements in this graph: transparent blue lines representing individual simulation paths, an orange line indicating the mean of 1,000 simulations, and a dark blue line reflecting the observed values of $ln\, Y(t)$. The large fluctuations in the blue line imply that the actual scenario had more extreme variations than the average simulation suggests, even occasionally trending beyond the packed line of possible simulations. This finding highlights potential limitations in the model or unexpected external shocks.

Table 8: Forecast and Actual Value of $\boldsymbol{ln\, Y(t)}$ for Each Month

Month	Forecast	Actual
Feb 2022	-3.561774198	-4.381149396
Mac 2022	-3.548004069	-2.962582393
Apr 2022	-3.570589642	-3.560208087

Month	Forecast	Actual
May 2022	-3.672109777	-4.017335604
June 2022	-3.713143261	-2.767202458
July 2022	-3.647443684	-3.152067746
Aug 2022	-3.592541359	-4.229444614
Sept 2022	-3.518365613	-4.454646051
Oct 2022	-3.560741936	-4.211715639
Nov 2022	-3.602067348	-4.039199603
Dec 2022	-3.579215366	-4.209795993
Jan 2023	-3.580380048	-4.345985996
Feb 2023	-3.566693221	-3.170657724
Mac 2023	-3.487691763	-2.739926535
Apr 2023	-3.509968966	-3.860489594
May 2023	-3.556682052	-4.180507498
June 2023	-3.531516065	-3.887962574
July 2023	-3.509249928	-3.737513557
Aug 2023	-3.554259934	-2.958084388
Sept 2023	-3.50935957	-2.515672654
Oct 2023	-3.557686113	-3.560208087
Nov 2023	-3.482504869	-3.112867505
Dec 2023	-3.612412362	-2.849997371
Jan 2024	-3.559204163	-3.331579908
Feb 2024	-3.668586554	-3.377968714
Mac 2024	-3.522526561	-2.700552525
Apr 2024	-3.520087843	-3.173266859
May 2024	-3.604532993	-3.817179007
June 2024	-3.602211734	-4.259230377
July 2024	-3.527943047	-3.182852349
Aug 2024	-3.511339069	-4.968147002
Sept 2024	-3.524786871	-4.34181802
Oct 2024	-3.580315889	-4.497427915
Nov 2024	-3.464942602	-3.962304506
Dec 2024	-3.568645156	-3.79136504

MAPE = 15.57%.

A MAPE of 15.57% implies that, on average, there are 15% discrepancies between the forecasts for ln Y(t) made by the model and the actual values. The MAPE value highlights the moderate accuracy of the model forecasts. Although it successfully predicts the overall trend of dividend yield evolution, there are significant discrepancies in the monthly changes as detailed in Table 8. Because it is a logarithmic scale, this implies that there are proportional discrepancies in the actual values of dividend yields. This suggests that it can be more helpful for predicting trends than for providing highly precise forecasts. Although they may be considered sufficiently accurate for exploratory purposes, forecasting inaccuracies can still be addressed.

4.5 Impulse Response Function (IRF) Analysis

Table 9: VAR Lag Order Selection Criteria

Lag	LR	FPE	AIC	SC	HQ
0	NA	1.61e-08	-12.26561	-12.21679	-12.24581
1	28.28510*	1.34e-08	-12.45544	-12.30898*	-12.39602*
2	9.239578	1.32e-08*	-12.47053*	-12.22643	-12.37151
3	4.969771	1.35e-08	-12.44625	-12.10450	-12.30761
4	3.256801	1.40e-08	-12.40610	-11.96672	-12.22786

Notes: * indicates the level of lag chosen.

Before conducting the IRF analysis, the appropriate lag length for the VAR model was determined utilising multiple selection criteria from Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Criterion (SC), as well as Hannan-Quinn (HQ). Based on the Table 9, the results indicated that lag 1 was selected by the majority of the criteria. Therefore, VAR(1) is selected as the optimal specification. This step ensured a balance between the model fit and degrees of freedom, which is particularly important for monthly data with a moderate sample size.

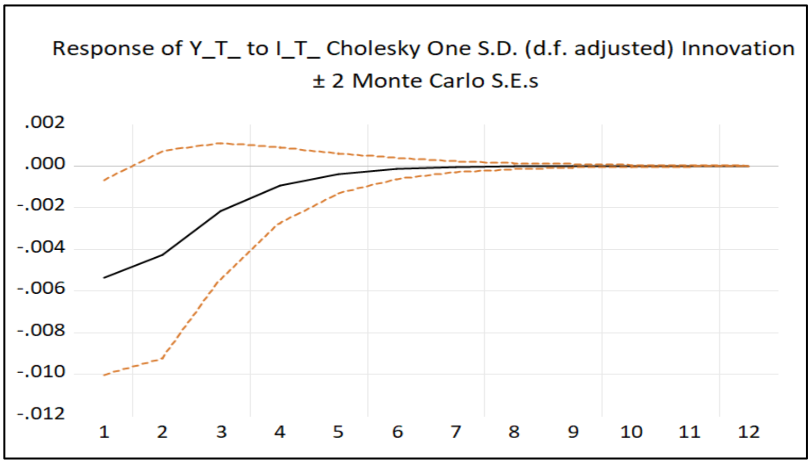

Figure 4: IRF Analysis of Inflation Shocks on Dividend Yield Graph

Figure 4 presents the dynamic impact of a one-standard-deviation innovation in inflation on dividend yield within 12 months. In the first month, the dividend yield declined by approximately -0.00536, indicating a negative short-run effect of inflation on dividend yield. Nevertheless, the impact decreased dramatically for the remaining months. At month 3, the impact had reduced to -0.00217, and by month 6, it had nearly reached zero at -0.00013. This pattern reflected a mean-reverting dynamic, in which the effect of the initial shock would not persist throughout the rest of the period. After month 7, the effect became negligible and insignificant as the confidence bands included zero. By month 12, the effect was insignificant, with an estimate of -8.22e-08, confirming that inflation shocks had no lasting influence on dividend yields after month 7.

The Monte Carlo confidence bands indicated that only the immediate impact was significant. After the first few months, the response lay well within the confidence bands, suggesting that the effect of inflation shocks on dividend yield was temporarily significant. The negative effects of the initial few months demonstrate that inflation shocks reduced dividend yields. This could occur due to increased uncertainty or higher input costs, thereby reducing expected payouts or delaying dividend adjustment. On the other hand, stock prices would respond more quickly to changes, thereby reducing the yield ratio. However, the effect was short-lived, disappearing within six months, indicating that the dividend yield dynamics were primarily driven by persistence rather than inflation shocks.

5.0 Conclusion and Future Research

This study demonstrates that adapting the Wilkie Investment Model to Malaysian data improved the accuracy of dividend yield forecasting compared to the original UK-based parameters because the parameters better reflected Malaysia’s economic conditions. The stationarity of the dividend yield and inflation series strengthened the reliability of the time-series approach, and the Malaysian-calibrated model yielded a MAPE of 16%. This result signified a reasonable predictive performance in forecasting dividend yields. Moreover, the IRF results indicate that inflation has a significant negative effect on dividend yield, which is initially negative before becoming constant.

Despite these contributions, this study has a few limitations that should be acknowledged. One limitation of this study is that the empirical analysis used a relatively short sample period. Although the sample period used in this study is sufficient to investigate the dynamic relationship between inflation and dividend yields and to support the forecasting exercise, a longer historical dataset may provide more robust parameter estimates. In addition, a longer dataset can better capture long-term economic dynamics. This expanded scope of data may enable the model to account for different economic cycles and potential structural changes. In response, future research may seek to extend this research by utilizing longer or more frequent datasets to further affirm the consistency of the established relationships. Similarly, future research may extend this model by including additional variables to enhance its explanatory power and by incorporating machine learning techniques to improve its predictive performance.

In addition, it is crucial to note that this study does not eliminate or clean outliers in the inflation data, as they reflect genuine effects that significantly affect inflation in Malaysia. These effects include the rise in inflation in early 2017 due to the dismantling of fuel subsidies and the increase in global oil prices (Ng, 2018). At the midpoint of 2018, political instability and transport prices affected inflation trends. The deflation in 2020 was caused by the COVID-19 pandemic and the collapse of global oil prices, whereas the inflation increase in 2021 was driven by base effects and higher prices for food and fuel products (Department of Statistics Malaysia, 2022).

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References

Agustin, D. (2019). *Analysis of the effect of inflation, interest rate, debt to equity ratio, return on assets, firm size, earnings per share, and asset growth on dividend payout ratio (Study of companies listed in the Jakarta Islamic Index 2014–2017)* [Undergraduate thesis, Muhammadiyah Surakarta University]. Muhammadiyah Surakarta University Repository.

Astivia, O. L. O., & Zumbo, B. D. (2019). Heteroskedasticity in multiple regression analysis: What it is, how to detect it and how to solve it with applications in R and SPSS. *Practical Assessment, Research & Evaluation, 24*(1). https://doi.org/10.7275/jx8q-7b20

Baillie, R. T., Diebold, F. X., Kapetanios, G., Kim, K. H., & Mora, A. (2024). *On robust inference in time series regression* (NBER Working Paper No. 32554). National Bureau of Economic Research. https://doi.org/10.3386/w32554

Bekaert, G., & Engstrom, E. (2008). *Inflation and the stock market: Understanding the "Fed model".* Columbia University & Federal Reserve Board.

Bergeron, C. (2024). Inflation, risk, and dividend growth. *SN Business & Economics*. Springer Nature. https://doi.org/10.1007/s43546-024-00674-x

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: Forecasting and control.* Holden-Day.

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science, 7*, e623. https://doi.org/10.7717/peerj-cs.623

Department of Statistics Malaysia. (2022, June 1). *Analysis of annual consumer price index 2021.* http://dosm.gov.my/portal-main/release-content/analysis-of-annual-consumer-price-index-2021

Engsted, T., & Pedersen, T. Q. (2016). *The predictive power of dividend yields for future* *inflation: Money illusion or rational causes?* CREATES Research Paper 2016-11, Aarhus University.

Glasserman, P. (2004). *Quasi-Monte Carlo.* In *Monte Carlo methods in financial engineering* (pp. 271–318). Springer.

Gwilym, O. A. P., Morgan, G., & Thomas, S. (2000). Dividend stability, dividend yield and stock returns: UK evidence. *Journal of Business Finance & Accounting, 27*(3–4), 261–281. https://doi.org/10.1111/1468-5957.00313

Hasan, F., Kayani, U. N., & Choudhury, T. (2023). Behavioral risk preferences and dividend changes: Exploring the linkages with prospect theory through empirical analysis. *Global Journal of Flexible Systems Management, 24*(4), 517–535. https://doi.org/10.1007/s40171-023-00350-3

Huber, P. (1995). *A review of Wilkie's stochastic investment model.* Staple Inn Actuarial Society.

Huber, P. J. (1967). The behavior of maximum likelihood estimates under nonstandard conditions. In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability* (pp. 221–233). University of California Press.

Ishak, N. (2015). *Aspects and applications of the Wilkie investment model* (Doctoral dissertation, Technische Universität Kaiserslautern).

Khan, M. I., Meher, M. A. K., & Syed, S. M. K. (2013). Impact of inflation on dividend policy: Synchronization of capital gain and interest rate. *Pensee Journal, 75*(11), 384–393. https://mpra.ub.uni-muenchen.de/51593

Lapeyre, B., & Jourdain, B. (2021). *Monte Carlo methods and stochastic algorithms.*

Lewis, C. D. (1982). *Industrial and business forecasting methods: A practical guide to exponential smoothing and curve fitting*. Butterworth Scientific.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix.

Econometrica, 55, 703–708.

Ng, M. S. (2018, February 15). Malaysia grew 5.9% in 2017 as inflation spiked on oil price rise. *The Malaysian Reserve.* https://themalaysianreserve.com/2018/02/15/malaysia-grew-5-9-2017-inflation-spiked-oil-price-rise/

Osman, A., Pyeman, J., Jaafar, M. S., Sundram, V. P. K., & Zakaria, S. (2024). Impact of inflation on dividend determinants and dividend payout. *European Proceedings of Social and Behavioural Sciences (EpSBS).* https://doi.org/10.15405/epsbs.2024.05.32

Pilotte, E. A. (2003). Capital gains, dividend yields, and expected inflation. *The Journal of Finance, 58*(1), 447–466. https://doi.org/10.1111/1540-6261.00530

Ruhani, F., & Mat Junoh, M. Z. (2023). Are stock market returns affected by financial market variables? Evidence from Bursa Malaysia by panel generalized method of moments. *International Journal of Ethics and Systems, 39*(3), 576–593. https://doi.org/10.1108/IJOES-11-2021-0201

Sahin, S., Cairns, A., Kleinow, T., & Wilkie, A. D. (2008). Revisiting the Wilkie investment model. *British Actuarial Journal, 14*(2), 327–392.

Thadani, P. (2021). Financial forecasting using stochastic models: Reference from multicommodity exchange of India. *Data Science in Finance and Economics, 1*(3), 196–214. https://doi.org/10.3934/DSFE.2021011

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica, 48*(4), 817–838. https://doi.org/10.2307/1912934

Wilkie, A. D. (1995). More on a stochastic asset model for actuarial use. *British Actuarial Journal, 1*(5), 777–964. https://doi.org/10.1017/s1357321700001331

Wilkie, A. D. (1986). A stochastic investment model for actuarial use. *Journal of the Institute of Actuaries, 113*(2), 279–393.