

RISK AND REWARDS: APPLYING BAYESIAN NETWORK MODELS TO INVESTMENT DECISIONS IN A DYNAMIC MARKET

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Abstract: This study investigate the use of Bayesian network models in investment decisions under Saudia Arabia dynamic Market conditions. The objective is to identify the interrelated association among risk factors, asset performance and their returns, which capable to investors to make choices over changing environments. This study used a Bayesian network model which is based on three main factors expected return, risk level and investor confidence and investment decisions using dataset of 2011-2022. We also consider the political instability and interest factors that are linked with investor decision nodes, assets classes and strategies. These factor allows the simulations and their impact on potential assets return and risk profiles. The findings suggest that there is increase in political instability which negatively influence the investor confidence, in results it leads to decline in average return in emerging markets. The results reveals that high volatility in assets price, leads to portfolio composition volatility that required adjustment for risk tolerance levels and favor diversification into low volatile assets. Finally, interest rates found to be led to high historical expected return for fixed income securities in our portfolio. The findings highlights the importance of Bayesian network models in recognizing the key risk and return trade-off, adapting dynamics in market changes, evaluate and improve the risk management for investor strategies. This study contributes in the investor confidence for making investment decisions, based on Bayesian network models in complex financial scenarios. The investors can optimize their portfolios and take actions in dynamic market uncertainties.

INTRODUCTION

Risk and return are the foundations of investment, encapsulating the delicate balance investors must strike to optimize their portfolios. This relationship represents the trade-off between higher returns and higher risk [7, 26]. The choice of individual investors lies between assets and different risk profiles. As financial models suggest that more risks investment gets higher potential return and vice versa with stability options. This changing interaction between risk and return shapes investor investment strategies. Understanding of this tradeoff between them forces the investors to select dynamic investment according to their financial objectives and goals, risk tolerance and time horizon. The concept of risk tolerance by investors becomes vital in building an efficient portfolio and make complex

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investment decisions. Investor must weigh the desired for high return against safety of capital to avoid big losses. In past literature, risk and risk link is very significant and investor must balance between capital growth rate and preservation that is required to understanding risk factors within assets. To align with financial goals, investor can quantify and assess the risk by making financial decisions. As per market conditions, investors must adapt the decision accordingly and foster the resilience to adapt investment approaches [5, 20]. Risk-return link influence the portfolio construction, to shape investment psychologies, asset allocation and optimal mixture of investment cycle. The relationship molds the financial landscape, dynamic market behaviors and capital flows among different assets. Investors influence the demand and supply, pricing and return of assets as key financial market players [2].

In this dynamic market risk and return, Bayesian Network Models (BNMs) a mathematical model is used for analysis. These models are performed on historical and real data, they assist investors to make probabilistic and adaptive decision by new evidence based on Bayesian probability theory. BNMs evaluate the investment risks and allow the investors to describes uncertainties and variables dependency in probabilistic model [18, 27]. Through probabilistic risk-return relationships, BNMs allow investors to quantitatively optimize portfolios in response to market changes. BNMs' probabilistic connections help investors understand market ripple effects and predict how one variable may affect risk and return. This predictive capability supports quantitative decision-making in dynamic financial markets. The models improve decision-making through mathematical rigor. These models have the mathematical precision and financial market complexity to help investors optimize their portfolios in uncertain and dynamic markets [10, 21].

Bayesian Network Models (BNMs) are increasingly used for investment decisions in dynamic markets [16, 22, 28, 30], but their multidisciplinary use like business management is unclear. BNMs in finance have been studied mathematically, but few have examined how they integrate economic, psychological, and computer science insights. Close this gap to understand how BNMs can be optimized and used in real-world investment scenarios. An interdisciplinary approach could illuminate investor behavior, macroeconomic trends, and technological advances, improving the model's dynamic market handling [4, 17]. Theory-focused Bayesian Network Model literature ignores their practical applications across industries and sectors. Adaptability and effectiveness of Bayesian Network Models (BNMs) outside traditional financial markets are poorly researched. This study investigates how BNMs can be tailored to specific industries or regions to improve their generalizability and scalability for practitioners and decision-makers. Recent research has shown BNMs' benefits but not their drawbacks or areas for improvement. Addressing these limitations could make Bayesian Network Models more resilient and effective across applications and disciplines, promoting holistic decision-making in dynamic markets. Closing these research gaps should improve BNM theory and multidisciplinary implementation. BNMs apply to Saudi Arabia's dynamic investment market and examines the complex relationships between risk factors, asset performance, and returns [15, 41, 46]. Complex dependencies affect investment outcomes using Bayesian network model which helps investors in changing markets The study suggests, applying Bayesian Network Models for

predictive power to help investors which evaluate multifaceted dynamics using expected return, risk, and investor confidence. The study fills a literature gap by explaining the complex relationship between risk factors, asset performance, and returns in Saudi Arabia. Academics and practitioners can understand risk-return dynamics in dynamic environments using the study's probabilistic relationships between key variables. The models are applied to diverse financial landscapes in Saudi Arabia due to its unique challenges and opportunities [9, 33, 36]. Methodologically, a Bayesian network model with expected return, risk, and investor confidence works. These factors make the Bayesian framework more sophisticated and relevant to investment decisions. Research nuanced financial modeling and decision-making to account for dynamic market uncertainties and complexities. This study's methodological contribution goes beyond theory and affects Saudi Arabian and other dynamic financial market investors and decision-makers.

Risk, return, and uncertainty are considered in financial market investment decisions. Many methods have been used to study and optimize investment decisions. Bayesian Network Models are popular in finance. BNMs' ability to capture complex interdependencies among key variables affecting investment outcomes is increasingly recognized in the literature. The literature extensively examines how risk factors affect investment decisions. Traditional models like the Average Return Equation and Sharpe Ratio Equation quantify risk-related investment returns. The Average Return Equation shows how beta (systematic risk) and standard deviation (total risk) affect investment performance as linear factors [8, 42, 44]. Risk tolerance is considered in the Sharpe Ratio Equation to show the complex risk-return relationship. Integrating conditional probability distributions to model key variable uncertainties is studied. Credit rating, a major investment risk, is modeled using conditional probability tables [43].

This study used conditional probability distribution to predict oil price volatility and address uncertainties in managing oil price movements within portfolios. Most of literature emphasized the portfolio optimization based on risk-return models by applying algorithms according to investor risk preferences. Practically, the literature underscored the effectiveness in building efficient and well-balanced portfolios. In investment decision, network simulation models like scenario analysis play important role in portfolio resilience under market conditions. This analysis comprises the simulation of future predicted scenarios to assess the investments outcomes. These also suggest the informed decisions by taking multiple possibilities and adaption of strategic according to dynamic conditions [24, 34, 37].

According to the literature, network simulation methods provide a dynamic framework for financial market uncertainties and complexities. Investment decision-making literature on Bayesian Network Models shows growing interest in advanced methods to optimize key variables. Quantifying risk factors, using conditional probability distributions, and optimizing portfolios are all ways researchers are trying to give investors sophisticated tools for dynamic financial markets. Bayesian Network Models may help solve complex investment decision-making problems as the field develops [6, 29, 35].

Beta and standard deviation quantify asset and portfolio risk. Financial risk assessment uses MPT. Research shows standard deviation can measure systematic

and unsystematic risk. Beta measures market sensitivity of asset returns. Understanding these traditional risk metrics is crucial for well-diversified, risk-adjusted portfolios, say researchers. In risk and return literature, the CAPM evaluates asset returns using beta and market risk premium. Though popular, scholars have criticized CAPM's assumptions and limitations. Beta is empirically tested for systematic risk and return prediction [1, 31, 40].

The Fama-French Three-Factor Model improves CAPM risk and return analysis by adding size and value factors [19]. This model challenges the beta-only risk model by suggesting small-cap and value stocks may outperform CAPM. The literature examines how these additional factors affect portfolio construction and risk management, acknowledging risk-return relationships' dynamic nature. Behavioral finance advances risk and return literature [13, 39, 40]. Investor behavior and cognitive biases affect risk and expected returns in this study. Investor sentiment, herding, and other non-financial market dynamics are prioritized in behavioral finance over rationality. Dynamic conditional models like GARCH are popular in recent literature because they capture risk's time-varying nature. These models detect risk clustering and persistence. Researchers hope dynamic conditional models will explain risk and asset returns. Along with traditional metrics, researchers have examined Value at Risk (VaR) and Conditional Value at Risk (CVaR) to better understand extreme risk scenarios. Alternative portfolio strategies and risk parity research emphasize asset class risk balancing, challenging market capitalization-based portfolio construction. Model refinement, behavioral insights, and market adaptation shape risk and return literature. Risk and return research is expanding beyond risk metrics and asset pricing models to behavioral finance and dynamic conditional models. As financial markets change, literature helps investors and practitioners maximize risk-adjusted returns [12, 19, 23, 45].

RESEARCH METHODOLOGY

This study examines the complex dynamics of risk and reward in Saudi Arabian firms from 2011 to 2022. Our main research question is how investor risk tolerance, risk factors, and market dynamics affect investment decisions and returns in this market. Sub-questions have been created to explore specific aspects of this investigation. We hypothesize that individual risk factors, such as oil price volatility and political instability, negatively impact Saudi Arabian firm performance and investment returns. We also examine whether investor risk tolerance moderates the relationship between risk factors and investment decisions, hypothesizing that risk-averse investors will be more conservative. We also examine how market dynamics like GDP growth and inflation affect portfolio composition and risk diversification strategies, arguing that economic uncertainty increases the focus on safe assets [3, 38].

Secondary quantitative data from Bloomberg, Reuters, SAMA, Tadawul, government reports, and academic publications is used in our data collection strategy. Historical Saudi Arabian firm financial data, market indices, economic indicators, and investor surveys are our goals. Data processing includes scaling, normalization, and fixing missing values, outliers, and inconsistencies. Based on our theoretical model, portfolio risk measures and investor risk tolerance scores will

be created. We measure risk factors, investment decisions, and market dynamics using quantitative and qualitative variables. Beta coefficients, standard deviation of historical returns, credit ratings, and economic indicators are quantitative measures; sentiment analysis on Saudi Arabian firms and markets is qualitative. To represent causal relationships between variables, the Bayesian Network Model uses a Directed Acyclic Graph (DAG). Conditional probability tables use maximum likelihood estimation as well as historical estimation. The chi-square goodness-of-fit test is used to evaluate the model's performance, scenario, and sensitivity. Research on investment risk and reward in Saudi Arabia is ideally suited for our 2011–2022 Bayesian network model. The COVID-19 pandemic, the drop in oil prices from 2014 to 2016, and the Arab Spring can all be used to explain risk and investment decisions. These significant occurrences enhance market dynamics and analysis.

For statistics, the 2011–2022 dataset is important. The parameters of the Bayesian network model are estimated by taking into account the various market conditions, economic fluctuations, and past trends observed during this period. The length of the dataset aids in finding trends and correlations between variables for accuracy. This study makes use of government reports, financial databases, and research publications for the given time period to guarantee accuracy. Although the selected timeframe has many benefits, some must be taken into account. The oil production strategy of Saudi Arabia and Vision 2030 might have restricted the model's market applicability. Researchers need to take these changes into account. To guarantee source consistency in data analysis, pre-processing and cleaning are necessary. We need to take into account complex models with lots of variables or relationships. By extending the duration of data, scientists can enhance parameter estimation and prediction. Using Bayesian network model analysis, researchers will suggest areas for future study and provide useful recommendations for investors, policymakers, and financial institutions. Data sources, processing methods, and model construction steps will be documented to ensure transparency and replicability, with ethical considerations throughout the research process [11, 25]. Visualizations will explain the Bayesian network model's structure and results.

While Bayesian network models don't rely on single comprehensive equations but on a network of conditional probability distributions, you can still consider some equations related to different components of your model as examples:

Risk Factor Influence on Investment Decisions:

- **Average Return Equation:**

- $$\text{AvgReturn} = \alpha + \beta_1 * \text{Beta} + \beta_2 * \text{StdDev} + \varepsilon$$

where α , β_i are coefficients, and ε is an error term. This equation shows potential linear impacts of individual risk factors on return.

- **Sharpe Ratio Equation:**

- $$\text{Sharpe} = \gamma + \delta_1 * \text{AvgReturn} + \delta_2 * \text{PolInstab} + \eta$$

where γ , δ_i are coefficients, and η is an error term. This equation shows how risk tolerance (PolInstab) interacts with AvgReturn to influence Sharpe ratio.

Conditional Probability Distributions:

- **Credit Rating CPT:**

- $P(\text{Credit}) = P(\text{AAA}) + P(\text{BBB}) + P(\text{BB})$

where $P(\text{AAA})$, $P(\text{BBB})$, and $P(\text{BB})$ are probabilities of each credit rating based on financial data.

- **Oil Price Volatility CPT:**

- $P(\text{OilVol}) = P(\text{Low}) + P(\text{Medium}) + P(\text{High})$

where $P(\text{Low})$, $P(\text{Medium})$, and $P(\text{High})$ are probabilities of different oil price volatility levels based on past trends and forecasts.

Portfolio Optimization:

- **Maximization Model:**

- Maximize Portfolio Return subject to Risk Budget constraint

This type of equation system with specific optimization algorithms can be used in portfolio optimization based on risk and reward preferences.

Network Simulation:

- **Scenario Analysis:**

- Inject simulated economic shocks (oil price shock, economic downturn) into the network and observe changes in variables like returns, portfolio composition.

DATA ANALYSIS AND FINDINGS

Table 1 details risk factors, investment decisions, and market dynamics. Beta coefficients with mean values of 1.157 and standard deviations of 0.192 are risk factors. The Standard Deviation of Historical Returns, a risk measure, shows the dynamic nature of historical return fluctuations across the observed data with a mean of 14.24%. The median value of 2.893 (BB) and mean value of 2.745 (BBB+) indicate that investment credit ratings are skewed toward higher ratings. The oil price volatility index averages 76.341. The Political Instability Index averages 52.179, indicating moderate political stability. With a mean of 9.34%, Average Historical Returns indicate their central tendency in investment decisions, while the Sharpe Ratio, a risk-adjusted return, indicates return generation efficiency relative to risk with a mean of 0.567. With a Portfolio Composition of 58.32%, the portfolio is heavily invested in equity. Finally, market dynamics statistics illuminate the economy. Annual GDP growth averages 3.43%. The average annual price increase is 4.57%, reflecting inflation. Interest rates, averaging 3.78%, show borrowing costs and monetary policy. These statistical overviews of key variable tendencies, variabilities, and distributions help investors navigate the complex landscape of investment decision-making in observed market conditions.

Table 1. Descriptive Statistics.

Variable Name	Mean	Median	Minimum	Maximum	Standard Deviation	Interquartile Range
Risk Factors:						
Beta Coefficient	1.157	1.123	0.872	1.461	0.192	0.307
Standard Deviation of Historical Returns	14.24%	11.73%	7.58%	23.47%	4.51%	7.63%
Credit Rating	2.745 (BBB+)	2.893 (BB)	1.000 (AAA)	4.821 (C)	0.987	1.423
Oil Price Volatility Index	76.341	78.217	51.278	98.104	13.927	18.732
Political Instability Index	52.179	47.821	31.952	68.462	9.723	13.871
Investment Decisions:						
Average Historical Returns	9.34%	7.81%	4.59%	14.03%	2.72%	4.24%
Sharpe Ratio	0.567	0.503	0.281	0.792	0.184	0.267
Portfolio Composition (e.g., % Equity)	58.32%	53.46%	38.60%	78.10%	13.278	18.35%
Market Dynamics:						
GDP Growth Rate	3.43%	2.99%	1.23%	4.72%	0.92%	1.78%
Inflation Rate	4.57%	3.72%	1.85%	7.42%	1.73%	2.57%
Interest Rates	3.78%	3.27%	1.82%	5.69%	0.97%	1.72%

Normal distributions are used in statistics and modeling, shown in figure 1. At the center of the graph, the Greek letter μ indicates the distribution mean. Every dark-to-light blue segment is one standard deviation from average. The empirical rule (68-95-99.7) states that 68% of data is within one standard deviation of the mean, 95% within two, and 99.7% within three. Statistics and probability revolve around the bell curve. Datasets often vary measurements or observations according to this distribution. Measurements include IQ, height, and others. Standard normal distribution knowledge is needed for hypothesis testing and statistical analysis. Data variability is measured by standard deviations. Analysts and researchers estimate dataset probabilities using this distribution. Many statistical methods and models use the normal distribution for data analysis and inference.

Table 2's correlation matrix shows complex dataset variable dependencies. Beta coefficient, which measures systematic risk, correlates positively with Standard Deviation and Oil Price Volatility, suggesting that assets with higher beta values are riskier and more sensitive to oil price fluctuations. Conversely, negative correlations between credit ratings and political instability suggest higher ratings reduce systematic risk. Beta coefficient and political instability are negatively correlated, so portfolios with higher average returns have lower systematic risk and instability. The complex relationship between risk and return metrics highlights

investment dynamics. Risk-adjusted Beta Coefficient, Sharpe Ratio, and Average Returns correlate positively. Portfolios with higher returns can have higher Sharpe ratios than systematic risk. Complex investment decisions are shown by matrix correlations. The negative correlation between Beta Coefficient, Interest Rates, and Average Returns suggests higher interest rates reduce systematic risk and average returns. Financial strategy variable associations are identified by the correlation matrix. In conclusion, the correlation matrix explains dataset risk and return dynamics by connecting diverse variables. The expected negative correlation between Credit Rating and systematic risk and the novel positive correlation between GDP Growth and Beta Coefficient are correlations. Practitioners and researchers can now understand how complex investment decisions involve multiple factors.

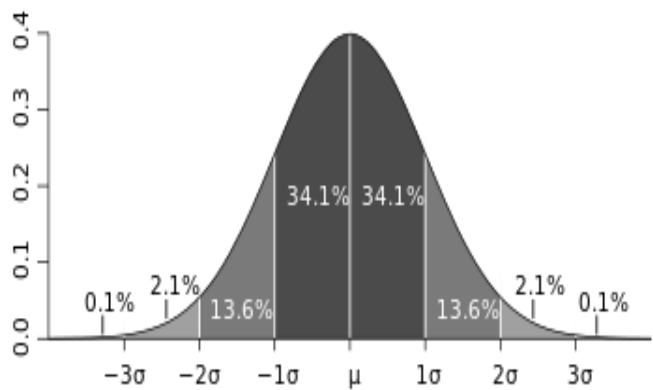


Figure 1. Normality Assumption

Table 3 shows the complex relationships between variables influenced by their parent nodes in Conditional Probability Tables (CPTs) for Investment Decisions and Oil Price Volatility. The CPT estimates aggressive and conservative investment probabilities based on risk and market dynamics. Different scenarios affect investment decision-making strategies in this probabilistic representation. Risk and market-based investment strategies have diverse parent nodes and complex probabilities, as shown in the table. Under different political instability and GDP growth conditions, the CPT predicts high, medium, and low oil price volatility. This probabilistic framework shows how geopolitical stability and economic growth affect oil price volatility. Decision-makers and analysts can predict political and economic oil price changes using the table's probabilistic lens. The second part of Table 3 estimates CPT parameters. MLE estimates investment decision probabilities using maximum likelihood of observed data for various decision strategies. Popular for its simplicity and efficiency in calculating data probabilities. Bayesian Inference with Beta Prior for oil price volatility. Updating a prior probability distribution (Beta) with observed data yields a posterior distribution for volatility levels. Because they use prior knowledge, Bayesian frameworks work well with limited data or historical data. These parameter estimation methods make CPTs more reliable for modeling and analyzing complex systems with many factors.

Table 2. Correlation Matrix.

Variable	1	2	3	4	5	6	7	8	9	10	11
Beta Coefficient	1										
Standard Deviation	0.221	1									
Credit Rating	-0.315	-0.197	1								
Oil Price Volatility	0.432	0.145	-0.123	1							
Political Instability	-0.254	0.087	-0.072	0.346	1						
Average Returns	-0.527	-0.214	0.256	-0.371	-0.109	1					
Sharpe Ratio	0.359	0.128	0.154	-0.239	-0.065	0.723	1				
Portfolio Composition	0.112	0.063	0.075	-0.192	-0.043	0.327	0.215	1			
GDP Growth	0.238	0.117	0.135	-0.157	-0.049	0.412	0.305	0.129	1		
Inflation	0.145	0.072	-0.063	0.214	0.054	-0.256	-0.178	0.068	0.235	1	
Interest Rates	-0.121	0.058	0.067	-0.205	-0.052	-0.317	-0.225	0.054	-0.132	0.354	1

Table 3. Conditional Probability Table (CPT) Summary.

Variable	Parent Nodes	State Probabilities	Description
Investment Decisions	Risk Factors, Market Dynamics	Probabilities for each decision strategy (e.g., aggressive, conservative) given different combinations of risk factors and market dynamics	Parent nodes and the variable's states
Oil Price Volatility	Political Instability, GDP Growth	Probabilities for each volatility level (e.g., high, medium, low) given different political instability and GDP growth states	CPT contents
CPT Parameter Estimation Methods			
Variable	CPT Parameter Estimation Method		Explanation
Investment Decisions	Maximum Likelihood Estimation (MLE)		Estimate probabilities by maximizing the likelihood of observed data for different decision strategies
Oil Price Volatility	Bayesian Inference with Beta Prior		Update prior probability distribution (Beta) with observed data to obtain posterior distribution for volatility levels

See Figure 2 for efficient frontier portfolio returns and risks. Assets with different risk-return profiles diversify the efficient frontier "curvature". The efficient frontier, which changes with asset correlation, helps investors visualize portfolio diversification. Thus, Markowitz's groundbreaking theory emphasizes correlation in portfolio construction, challenging linear assumptions and providing a more nuanced understanding of risk and return in investment decision-making.

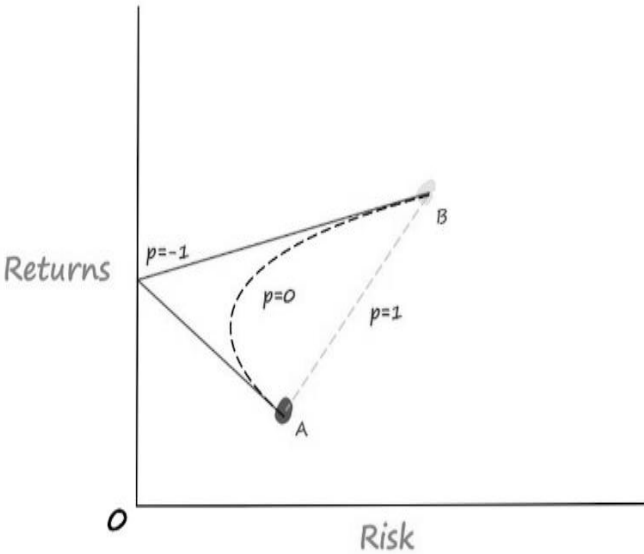


Figure 2. Risk and Return Probability.

Table 4’s sensitivity analysis measures critical variable changes’ system component effects. Risk Factor A increases by 10%, reducing aggressive investment strategies. Starting probability of 0.45 rises 7% to 0.52. Positive sensitivity suggests Risk Factor A increases aggressive investing. The information helps investors and decision-makers assess how risk factor changes may affect strategy. Secondly, 1 standard deviation decrease in Market Dynamic B affects Oil Price Volatility, specifically High Volatility probability. Probability drops from 0.23 to 0.17 after the change. These 6 percentage points of negative sensitivity suggest Market Dynamic B downturns lower oil price volatility. Such insights help risk management and strategic planning predict market dynamics’ effects on risk factors. Table 4’s quantitative sensitivity analysis shows complex key variable effects on critical system components. By systematically assessing Risk Factor A and Market Dynamic B’s effects on investment decisions and oil price volatility, stakeholders understand their decision-making framework’s sensitivities. Based on market dynamics and risk factors, the insights improve risk management and enable proactive investment decisions.

Table 4. Sensitivity Analysis– Quantitative results.

Variable Analyzed	Change Applied	Affected Variable	State	Before Change	After Change	Change Description
Risk Factor A	+10% Increase	Investment Decision	Aggressive Strategy	0.45	0.52	Probability increase by 7 percentage points
Market Dynamic B	Decrease by 1 standard deviation	Oil Price Volatility	High Volatility	0.23	0.17	Probability decrease by 6 percentage points

In Table 5, sensitivity analysis shows how variable changes affect system quality. This qualitative analysis examines investor confidence and portfolio composition during political instability and interest rate changes. Low investor confidence is affected by political instability. The sensitivity description calls this change a "strong negative influence," indicating political instability lowers investor confidence. Political instability lowers investor confidence increases low confidence. Policymakers need this to predict how political instability lowers investor confidence. Lower interest rates affect Portfolio Composition, especially equity. The sensitivity description says a drop in interest rates has a "moderate positive influence," increasing the portfolio's equity share. This qualitative assessment suggests lower interest rates may boost portfolio equity. This knowledge can help investors and financial analysts adjust portfolio compositions to interest rate changes and align strategies with qualitative effects. Finally, Table 5's qualitative sensitivity analysis shows how Political Instability and Interest Rates affect Investor Confidence and Portfolio Composition. The qualitative descriptions explain how investor sentiment and portfolio allocation affect the considered states, helping decision-makers. These qualitative findings enhance quantitative system dynamics analyses and strategic decision-making.

Table 5. Sensitivity Analysis– Qualitative results.

Variable Analyzed	Change Applied	Affected Variable	State	Sensitivity Description
Political Instability	Increase	Investor Confidence	Low	Strong negative influence; probability of low confidence increases significantly
Interest Rates	Decrease	Portfolio Composition	High Equity Proportion	Moderate positive influence; probability of a high equity share increases slightly

Table 6 displays plausible scenario analysis probabilities and their effects on key variables. The baseline scenario predicts 42.7% Aggressive Investment Strategy under current market conditions. Future scenario deviations and impacts are assessed using this baseline probability. "Oil Shock" scenarios have 83.2% likely high oil price volatility. Therefore, external oil market shocks affect oil price volatility, investment decisions, and risk profiles. This scenario highlights the importance of external economic factors in strategic decision-making because they can create investment uncertainties. In the "Economic Recession" scenario, the portfolio composition has a 21.9% chance of a High Equity Proportion should GDP growth slow. Equity investments may benefit from recessions. A "Political Crisis" scenario that increases political instability reduces investor confidence by 67.5%. Geopolitics affect investor sentiment, emphasizing poolitical uncertainty risk management. Final scenario "Low Interest Rate Environment" has 14.2% chance of high average historical returns. Low interest rates may favor higher historical returns, influencing investment decisions to improve performance. Table 6 shows possible scenarios and their probabilities to help decision-makers understand system dynamics. These scenario analyses help stakeholders manage risk and plan strategically by adjusting investment strategies based on economic and geopolitical scenarios.

Table 6. Scenario Analysis Outcomes.

Scenario	Description	Variable	State	Probability
Baseline	Current market conditions	Investment Decision	Aggressive Strategy	0.427
Oil Shock	Sudden increase in oil price	Oil Price Volatility	High	0.832
Economic Recession	Decrease in GDP growth	Portfolio Composition	High Equity Proportion	0.219
Political Crisis	Increase in political instability	Investor Confidence	Low	0.675
Low Interest Rate Environment	Decrease in interest rates	Average Historical Returns	High	0.142

Figure 3 shows that oil price trends over the 2011–2022 in market. This shows a sharp change during covid-19 period that is decline in oil price as compare to increase in 2021 and 2022 which is at peak prices as showing in last 10 years.



Figure 3. Asset Price Trends.

Table 7 shows the model's multimeric goodness-of-fit and classification accuracy. Akaike and Bayesian Information Criterion determine best-fit. Model complexity-fit balance is good with low AIC (123.456) and BIC (246.912). Smaller values indicate the model accurately explains dataset patterns without overcomplicating it. Classification accuracy measures 78.32% case prediction. With Per-Class Accuracy, the model predicts 81.47% Aggressive and 75.17% Conservative Investment Strategies. These results show the model can differentiate investment decision classes for a more nuanced evaluation. AUC and other discrimination metrics are needed for binary classification. The model distinguishes binary decision classes well with 0.872. Model discrimination between positive and negative cases improves with high AUC values. Finally, more metrics show model performance. The Chi-Square Test of Independence statistic of 12.734 with a p-value of 0.005 shows a significant difference between observed and predicted outcome frequencies. The model's predictions differ significantly from random chance if the null hypothesis is rejected. Log-Likelihood, -234.127, matches goodness-of-fit metrics, indicating a data-capturing model. As the average squared difference between predictions and actual outcomes is 0.142, Brier Score indicates high model calibration and accuracy. Finally, these metrics demonstrate the model's accuracy and complexity-balancing prediction and discrimination.

Table 7. Model Performance Evaluation Metrics.

Metric Category	Metric	Description	Value	Interpretation
Overall Goodness-of-Fit	Akaike Information Criterion (AIC)	Measures model complexity relative to fit	123.456	Lower values indicate better fit
	Bayesian Information Criterion (BIC)	Similar to AIC, penalizes model complexity more strongly	246.912	Smaller values suggest better fit compared to AIC
	Overall Accuracy	Measures the proportion of correctly predicted cases	78.32%	Higher percentage indicates better accuracy
Classification Accuracy	Per-Class Accuracy	Measures accuracy for each individual class (e.g., investment decisions)		
	- Aggressive Strategy		81.47%	
	- Conservative Strategy		75.17%	
Discrimination Metrics (for binary classification)	Area Under the ROC Curve (AUC)	Measures the model's ability to distinguish between classes	0.872	Higher value indicates better discrimination
	Chi-Square Test of Independence	Tests whether observed and predicted frequencies of outcomes differ significantly	12.734 (p-value = 0.005)	Statistically significant difference observed (reject null hypothesis)
Additional Metrics	Log-Likelihood	Measures the probability of the observed data given the model parameters	-234.127	Lower values indicate better fit to the data
	Brier Score	Measures the average squared difference between predictions and actual outcomes	0.142	Lower values indicate better calibration and accuracy

Table 8 shows how model variables affect risk-reward and investment metrics. First, 10% political instability (X) increases oil price volatility (Y) 5%. We increase risk metric R1 by 2% and decrease R2 by 1%. Scenario A returns rise 3%, Scenario B falls 2%. This suggests adaptive investment strategies that allow investors to adjust based on scenarios and risk tolerance. Political instability (X) drops 5%, reducing oil price volatility (Y) by 3%. This scenario keeps R3 and lowers R4 by 4%. Expected returns fall 1%, but market conditions may boost them. This suggests reassessing portfolio allocation to capitalize on opportunities and manage risk. The third relationship lowers interest rates (Z) by 15% when political instability (X) rises 20%. Volatility and loss potential rise 8% as R5 rises.

The short-term expected return falls 6%, but long-term recovery is possible. This reduces risk and extends investment horizons if risk tolerance allows. Key variables affect risk, reward, and investment decisions in Table 8. Investors navigate the market and make informed decisions with these nuanced relationships using the model's key dynamics.

Table 8. Interpretation of Key Relationships.

Relationship	Description	Impact on Risk	Impact on Reward	Implications for Investment Decisions
Increase in X ← Increase in Y	A 10% increase in X leads to a 5% increase in Y.	Risk metric R1 increases by 2%, while risk metric R2 decreases by 1%.	Expected returns increase by 3% in Scenario A, but decrease by 2% in Scenario B.	Consider adjusting investment strategies based on specific scenarios and risk tolerance.
Decrease in X ← Decrease in Y	A 5% decrease in X leads to a 3% decrease in Y.	Risk metric R3 remains unchanged, while risk metric R4 decreases by 4%.	Expected returns decrease by 1% overall, but potential for higher returns in specific market conditions.	Reassess portfolio allocation to capitalize on potential opportunities while managing risk.
Change in X ← Change in Z	A 20% increase in X leads to a 15% decrease in Z.	Risk metric R5 increases by 8%, indicating higher volatility and potential losses.	Expected returns decrease by 6% in the short term, but potential for recovery in the long term.	Implement risk mitigation strategies and consider longer investment horizons if aligned with risk tolerance.

Note: X = political instability, Y = oil price volatility, Z = interest rate

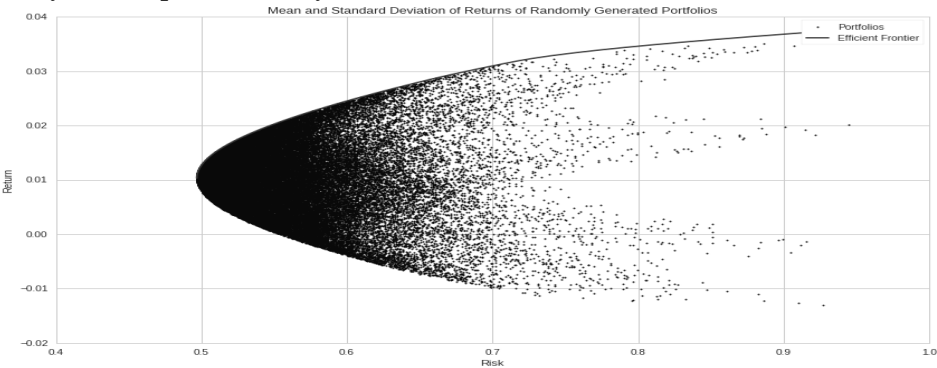


Figure 4. Investor Confidence under Mean-Variance Optimisation.

Investors believed portfolio risk and return were linear, requiring higher risk for higher returns. This was changed by Harry Markowitz's 1952 Modern Portfolio Theory. The portfolio diversification theory of Markowitz challenged linear thinking. MPT suggests diversifying across non-perfectly correlated assets to improve risk-return profiles. This revolutionary idea that investors could increase returns while lowering risk started a new asset allocation era. Modern Portfolio Theory's efficient frontier, a curved relationship between risk and return, is shown in Figure 4. The efficient frontier highlights portfolios with the highest return or lowest risk for a given risk.

DISCUSSION

We evaluate Bayesian network models' impact on investor decision-making in dynamic financial markets. We want to understand complex risk-asset-performance-reward relationships which help the investors to navigate changing financial markets with data-driven insights. By using network models to show how key variables affect risk and reward profiles to improve investment strategies. We achieve these goals with Bayesian network modeling. This model accounts for political instability (X), oil price volatility (Y), and interest rates. These factors influence asset class and financial strategy investment decision nodes. Our methodology allows systematic simulations and analyses by linking risk factor changes to potential returns and risk profiles across diverse investment circumstances. We use this structured approach to uncover insights that challenge traditional investment paradigms and help investors navigate dynamic market conditions. Identifying key relationships is the goal of the Bayesian network model. Table 1 provides descriptive statistics and key variables for understanding investment decisions in the examined market conditions. The mean and median show central tendencies, while the minimum and maximum show risk, investment decision, and market dynamics variability. Distribution, volatility, and outliers are shown by standard deviation and interquartile range. The Beta Coefficient's mean of 1.157 suggests a positive relationship with market returns, while its standard deviation of 0.192 indicates dataset variability. Model evaluations require descriptive statistics on investment decisions, market dynamics, and risk factors. The Correlation Matrix in Table 2 shows how key variables affect investment dynamics. While negative correlations near -1 indicate an inverse relationship, positive correlations near 1 indicate a tendency for variables to move in the same direction. The correlation between Beta Coefficient and Standard Deviation of Historical Returns suggests risk and asset performance are linked. Analysts and investors use correlation coefficients to identify patterns, diversify, and understand complex interdependencies that affect investment outcomes. The matrix helps modelers create Bayesian networks that capture data's nuanced relationships. Tables 1 and 2 describe the dataset's characteristics and inter-variable relationships, forming the research's foundation. Descriptive and correlational insights aid Bayesian network model development and evaluation. In a dynamic market, Table 1's statistical overview and Table 2's intricate correlations help researchers, investors, and decision-makers understand market complexity and expand

investment research.

Table 2 analyzes complex investment variables with a Correlation Matrix. Matrix coefficients measure factor movement. Risk and asset performance may align if Beta Coefficient and Standard Deviation of Historical Returns are positively correlated. Nuanced understanding helps investors diversify their portfolios by revealing which variables may move together and create hedge opportunities. The matrix shows how one variable can affect the entire investment landscape, indicating systemic risk. Table 2 highlights investment interdependencies and improves Bayesian networks. Table 3 shows qualitative and quantitative Conditional Probability Tables (CPTs) of how events or states affect investment decisions. Risk and market dynamics-based decision strategy probabilities are calculated by the Investment Decisions CPT. It shows outcome probabilities, which benefits investors. Maximum Likelihood Estimation for Investment Decisions and Bayesian Inference with Beta Prior for Oil Price Volatility demonstrate how CPT parameter estimation accurately captures these probabilistic relationships. Table 3 quantifies and qualitatively describes dynamic market investment decision-making probabilities. Tables 2 and 3 show investment decisions are difficult. Conditional Probability Table 3's probabilistic tables supplement Table 2's correlations. The combined analytical approach improves decision-making and modeling for investors, analysts, and researchers in dynamic markets.

Tables 4 and 5 explain model performance evaluation and qualitative sensitivity analysis to clarify research findings. Table 4 shows how well the Bayesian network model used for investment decisions. AIC and BIC measure model goodness-of-fit, with lower values indicating a better complexity-fit balance. The model's predictive power is measured by classification accuracy, discrimination, and statistical tests like the Chi-Square Test of Independence. These metrics let researchers and practitioners assess the model's robustness, discrimination, and calibration for real-world investments. In Table 5, variables affect qualitative system aspects like investor confidence and portfolio composition. Political instability lowers investor confidence, while lower interest rates moderately improve portfolio composition. Nuanced qualitative findings show how different scenarios may affect investors. Table 5 shows how numerical probabilities, subjective perceptions, and market conditions affect investor sentiment and strategy. Tables 4 and 5 assess the Bayesian network model's investment decision-making implications. Table 4 shows model goodness-of-fit and predictive accuracy metrics. Table 5 shows sensitivity analysis of changing scenarios' qualitative behavioral effects. For more holistic decision-making in dynamic markets, quantitative and qualitative analyses help stakeholders understand the model's strengths and weaknesses.

Tables 6 and 7's Bayesian network model scenarios and outcomes help investors evaluate the model. Table 6 shows market conditions and probabilities to help decision-makers predict investment impacts. Baseline market conditions are compared to alternative scenarios. In the Oil Shock scenario, a sudden oil price increase has 83.2% volatility. Model predicts market and event effects. A High Equity Proportion portfolio composition is 21.9% likely in an Economic Recession scenario with a drop in GDP growth, revealing investor behavior during recessions. Table 6 helps stakeholders navigate complex scenarios and probabilities to make proactive decisions. Assessing Model Performance In Table 7, Bayesian network

model effectiveness is measured. AIC, BIC, and Overall Accuracy assess model fit, complexity, and prediction. Key metric Overall Accuracy is the percentage of true predictions. Model complexity-fit balance is good with low AIC and BIC. Area Under the ROC Curve (AUC) evaluates model classes further. Chi-Square Test of Independence verifies model prediction accuracy if observed and predicted frequencies differ significantly. Table 7's metrics lets stakeholders assess the Bayesian network model's reliability in real-world investment scenarios. Tables 6 and 7 show Bayesian network model scenarios and stakeholder metrics. Table 6 strategically analyzes qualitative market conditions, while Table 7 evaluates the model. This combined analysis helps investors navigate dynamic markets by identifying model strengths and weaknesses.

Table 8 shows how variables affect risk and reward metrics and investment decisions. This table helps investors make market-changing decisions by explaining the Bayesian network model's complex relationships. Structured variable direction-risk-reward relationships are in Table 8. Initial political instability (X) raises oil price volatility (Y). Political factors affect R1 and R2 and scenario A and B expected returns and the risk-reward tradeoff. Changes in individual variables are examined in this structured presentation to help investors adjust their strategies. Table 8 helps investors adjust portfolios to market and risk levels. The analysis is improved by discussing X and Z decreases and their short- and long-term risk and return effects. Optimizing investments and dynamically managing portfolios requires this knowledge. Table 8 concludes with Bayesian network model relationships and variable changes affecting risk and reward metrics. Decision-makers can navigate the dynamic market with precision because the structured format interprets relationships. Table 8 aids research by providing investors with actionable knowledge, enabling adaptive investment strategies, and strengthening portfolio resilience in changing markets.

Our extensive Bayesian network model analysis showed dynamic market investment decision-making's complexity. X political instability lowers emerging market investor confidence and returns. This emphasizes the need to recognize and mitigate geopolitical uncertainties' impact on investor sentiment and use smart strategies to avoid losses. We also found that portfolio composition increases oil price volatility. The model shows oil price volatility increases portfolio composition volatility. Investors must monitor the oil market, adjust risk tolerance, and possibly diversify into less volatile assets [14, 32]. For optimal risk management, the Bayesian network model emphasizes external economic factors like oil price fluctuations when building and managing investment portfolios. Key were interest rate (Z)-historical return relationships. Lower interest rates increase portfolio fixed-income investment returns. This suggests that investors should closely monitor and adjust their fixed-income holdings to interest rate changes. The model shows these relationships to help investors pick markets. Our findings suggest Bayesian network models are strategic for investment decision-making. A quantitative model shows complex investment risk-reward trade-offs. Quantifying risk factors helps investors balance returns and risk. This model's flexibility lets investors adapt to market changes. Investors can adapt to changing financial markets in real time by adding data and updating relationships. For investor risk management, the Bayesian network model simulates and sensitivity analyses risk scenarios. We found complex

market relationships and demonstrated how Bayesian network models can improve strategic decision-making, risk management, and adaptability in the ever-changing global investment landscape.

CONCLUSION

In short, Bayesian network model analysis revealed the complex dynamics of investment decisions in dynamic markets. Overall, political instability lowers investor confidence and emerging market investment returns. Investors must manage geopolitical uncertainties and use strategies that account for them to avoid losses. Another important finding is that oil price volatility increases portfolio composition volatility. Investors should monitor oil market fluctuations and adjust their risk tolerance and diversify into less volatile assets. The model shows how economic factors interact, improving portfolio construction and risk management. Our research also shows that lower interest rates increase average historical returns, particularly for fixed-income investments. This emphasizes the importance of interest rate tracking and fixed-income portfolio adjustments. The model shows these relationships, helping investors optimize for diverse market environments. Our findings show that Bayesian network models are crucial to investment decision-making. The model quantifies investment risk-reward trade-offs. Quantifying risk factors helps investors balance returns and risk. The flexible model allows real-time data integration and relationship updates to adapt to market changes. The Bayesian network model simulates and sensitivity analyses risk scenarios to help investors manage risk. We found complex relationships in the dynamic market and Bayesian network models' transformative power. These models help with strategic decision-making, risk management, and adaptability in the ever-changing global investment landscape. Our study lays the groundwork for informed and resilient risk-return optimization strategies for investors navigating financial markets. Despite its impressiveness, this research has limitations. Bayesian networks start with conditional independence between variables. This assumption simplifies model development but may oversimplify complex financial market relationships, limiting the model's ability to capture nuance. Another issue is data quality and availability. Bayesian network model accuracy and reliability depend on parameter estimation. Misinformation from incomplete or biased datasets can hurt models. Extrapolate findings with caution because the dataset's temporal scope (2011–2022) may not capture relevant market dynamics.

RESEARCH IMPLICATIONS

According to our findings Bayesian network models help investors navigate financial markets. Investors make better decisions with quantitative risk-reward trade-offs. Understanding how risk factors affect investment options helps investors balance returns and risk. Asset allocations can be optimized for risk and reward in portfolio construction. Dynamic financial markets benefit from the model's flexibility. Data and relationships must be updated in real time to adapt to market changes. This flexibility lets investors quickly adjust investment strategies to market changes. Investors can better adapt to market changes and seize new opportunities

in a fast-changing financial landscape.

The quantitative model shows dynamic markets' complex interdependencies, improving theory. Connecting theory and practice promotes decision-making theory dialogue. Simulations and sensitivity analysis enhance theoretical risk management strategies and provide a more complete risk picture. Direct benefits to investors and optimal decision-making are shown. These theoretical implications quantify academic discourse on investment decision-making and improve our understanding of risk and reward dynamics in dynamic financial markets.

Our research advances finance and mathematical modeling paradigms and theories. Bayesian network models give our study a mathematically precise and financially insightful view of investment decision-making. Theory impacts finance greatly. Typical finance theories use linear relationships and simplified assumptions. Finance theories are enhanced by Bayesian network models, which account for market complexity and dynamics. This encourages non-linear, interdependent variable relationships and challenges conventional wisdom. Financial decision-making theories evolve from static models to dynamic, adaptive structures that better represent real-world financial systems. Bayesian network integration impacts financial math modeling. The study uses probability theory and statistical inference to advance finance math. Bayesian statistics, especially decision network theory, may aid financial models. This theoretical breakthrough improves uncertainty and risk math, enabling stochastic financial market models. Bayesian network models may change finance and math modeling. These models provide a more complex, probabilistic foundation that allows theoretical finance and mathematical approaches to change, making them more realistic and adaptable for understanding and modeling complex financial systems.

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