Prediction and Optimization of Export Opportunities Using Trade Data and Portfolio

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Abstract. The modern portfolio theory targets to achieve a safe investment while extracting maximum profit. Its use in exploring export opportunities is undocumented. Traditionally, the gravity model of trade is widely used to calculate trade flows while the prediction of trade flow was based on application of time-series prediction algorithms on historical trade data. The proposed research introduced the risk involved in the trade opportunity as a quantitative factor determined by product complexity and gravity model of trade, while predicting the optimal export commodities to maximize profit and minimize risk. Improvement in trade prediction accuracy using portfolio optimization methods as compared to other previously documented methods is also reported. The results indicate MSE of 0.161 and 0.239 using Black Litterman model and CAPM against 1.226 and 1.026 using the traditional Holt and Grey models respectively. The results are supplemented by the level of risk attached to each commodity, to classify the optimal products for export investment.

Keywords: Export prediction · Portfolio theory · Product complexity · UN COMTRADE data · Gravitational theory · Textile · Black-Litterman model · Trade forecasting

1 Introduction

Countries do not remain in isolation, they import commodities to fulfill their requirement which are not produced or in the shortage, and in return they export the commodities/goods which are surplus. Exports of a country are proportional to its economic development and GDP. In order to analyze exports trade data is standardized using the Harmonized Systems (HS) of tariff nomenclature to globally standardize a trade item into number and name to classify the product.

Risk is considered a major component in trade analytics [1]. World Trade Statistical Review 2018 [2] by World Trade Organization (WTO), while forecasting an improvement in trade flows warned for the inevitable consequences in case of triggering of the risk factors. At macro-level, trade risks include national policy changes, tensions between countries, military conflicts etc. These risk factors lead to weak investment spending and consequently lowered world GDP.

Risk is directly related to Product complexity [3] due to the disruption cost of complex items. It has direct and indirect impacts on trade. Dominik et al. [4]

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documented the linear relationship between the product complexity and economic development of the country. Product complexity therefore, poses a more serious risk for developing countries. As we increase the product complexity of a product, we also tend to increase the life cycle cost of that product. The increase in the direct costs due to the increase in product complexity was also documented [5]. The more complex a certain product the costlier and complicated it becomes, which increases the direct costs associated with production and development e.g. time, product analysis etc. GDP of trading countries and the distances between them, explained in the gravity model, define the factors which determine the trade flow between the countries [6]. This was first displayed in 1962 by Jan Tinbergen, who suggested that the span of reciprocal exchange streams between any two nations can be approximated by utilizing the 'gravity equation'. Relative size is dictated by the present GDP, and financial vicinity is controlled by profession costs that the all the more monetarily "distant" the more prominent the trade costs, similarly role of gravity model was defined by different researchers [7, 8] to consider the impacting factors of trade.

The objective of this research was to identify the gaps in the current export investment model of all commodities especially textile industries and introduce a more robust framework which quantitatively evaluates the risk factors involved in trade of specific sector and optimize the system which maximize profits and minimize risk. The modern portfolio theory explains the optimal portfolio concepts that investor will invest on the basis of maximizing their profit for their selected tolerated level of risk to determine the suitable commodities with their weightage in a portfolio. The Fig. 1 explains how the optimal portfolio works. Along the line of the curve the ideal risk portfolio is depicted which shows a perfect trade-off between risk and returns.

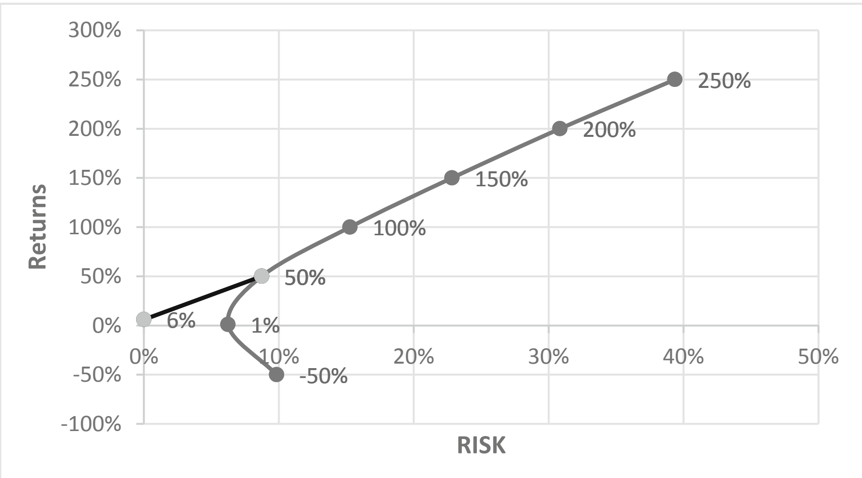

Fig. 1. Efficient frontier of portfolio

The modern portfolio methods used in this research are Markowitz portfolio [9], CAP M. [10] and Black-Litterman [11] model which incorporate qualitative and quantitative analysis on the dataset extracted from UN comtrade [12]. The database is from United Nations international trade statistics. Annual international trade statistic data including details of commodities category with partner country are provided to United Nation static division (UNSD) by more than 170 countries. It is the biggest repository of international trade data. Comtrade data by clause 3 & 16 of United Nation department of economic and social affairs statistic division are permissible to use in research. It contains more than 3 billion trade data record since 1962.

The rest of the paper is classified as follows. Brief background research is provided in Sect. 2 that overviews the related work. Section 3 presents the proposed algorithm used on the dataset. Results and implementation are discussed in Sects. 4 and 5 gives the analysis of results and future work.

2 Background/Related Work

Uribe et al. [13] did an informational approach to forecast of inter-regional trade flows. They used RAS method for trade flow analytics to project features for trade flow forecast of the years 1938 to 1960. Xia et al. [14] worked on China export by using holt model on trade data. They worked on the export of garments & textile products to provide the forecast of textile industry with MAPE of 13.25-34.99. Xie et al. [15] introduced genetic algorithm to optimize Grey modeling to predict the aggregate volume of trade. They presented a technique in view of hereditary calculation to optimize parameters of grey model GM (1, 1) through genetic algorithm. Kong et al. [16] worked on the long-term export prediction of textile industry and discovered the market of clothing still developed quickly in three to five years. Dabin et al. [17] took the trade data of Hubei province of China to forecast custom export and showed increased accuracy of holt model than the traditional econometric model.

In this way researchers [18, 19] forecasted trade data by using different models defined above to increase the prediction accuracy or defining the future potential of the trade commodity. Different researches [3–5] defined the role and impact of product complexity and gravity model [6] on trade. Currently, no published work was available, which could define the opportune commodities for investors to invest with control on the risk parameter. The major factors which are used to calculate the export opportunity include trade data, government policies, gravity equation and product complexity. Expert opinion has a major role to forecast trade of a country. Several researches [20–22] provide theoretical parameters like demographic change, investment, technology, energy and other resources, institution etc. strongly impact on trades. For this problem we used an approach to multiplex all the factors and utilize modern portfolio theory and Black-Litterman model to incorporate expert opinion based on commodity complexity, gravitational theory, law, government policies etc. with past data to present a unique idea to forecast trade and find opportunities for capitalist to invest in trade and gain risk control returns.

3 Proposed Algorithm

In the proposed work Markowitz portfolio optimization [9] and Black-Litterman model [11] was utilized from the perspective to calculate expected return and risk related to each commodity of export using trade data, gravitational theory and product complexity data for the expert to incorporate their views in a model for better accuracy and minimum risk. Figure 2 shows the conventional forecasting model and the proposed model shown in Fig. 3 has classified the trade optimization and asset allocation into 2 main categories. The quantitative method incorporates the algorithms which only use the historical trade data to make asset allocation and risk calculation whereas the quantitative method additionally also employs expert opinion in the form of a numeric matrix to add the expert views in the algorithm.

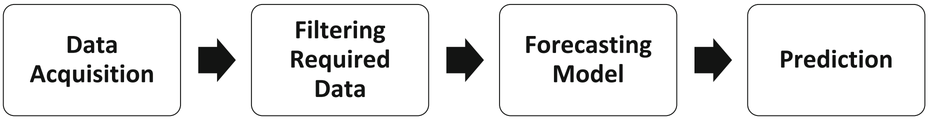

Fig. 2. Conventional forecasting model

3.1 Markowitz Portfolio Optimization

We used Markowitz mathematical framework to diversify investment and finding opportunities in different trade commodities to boost the profit and having the information of risk involved to each trade commodity, to assist investors in decision making of investment to gain high returns and defined risk. The overall return of the portfolio is calculated by Eq. (1), there are N commodities. r_{ct} is the return at time t on an investment in a commodity C; d_{ct} is the rate of return of commodity C at time t and W_c the weightage of investment.

$$R = \sum_{t=1}^{\infty}\sum_{c=1}^{N} d_{ct} r_{ct} W \tag{1}$$

$$R = \sum_{c=1}^{N} W_c \left(\sum_{t=1}^{\infty} d_{ct} r_{ct} \right) \tag{2}$$

$R_c = \sum_{t=1}^{\infty} d_{ct} r_{ct}$ is the return of c^{th} commodity, Therefore

$$R = \sum XcRc \tag{3}$$

In this equation X_c and R_c are independent. Since $X_C \geq 0$ for all C and $\Sigma Xc = 1$ for maximize return.

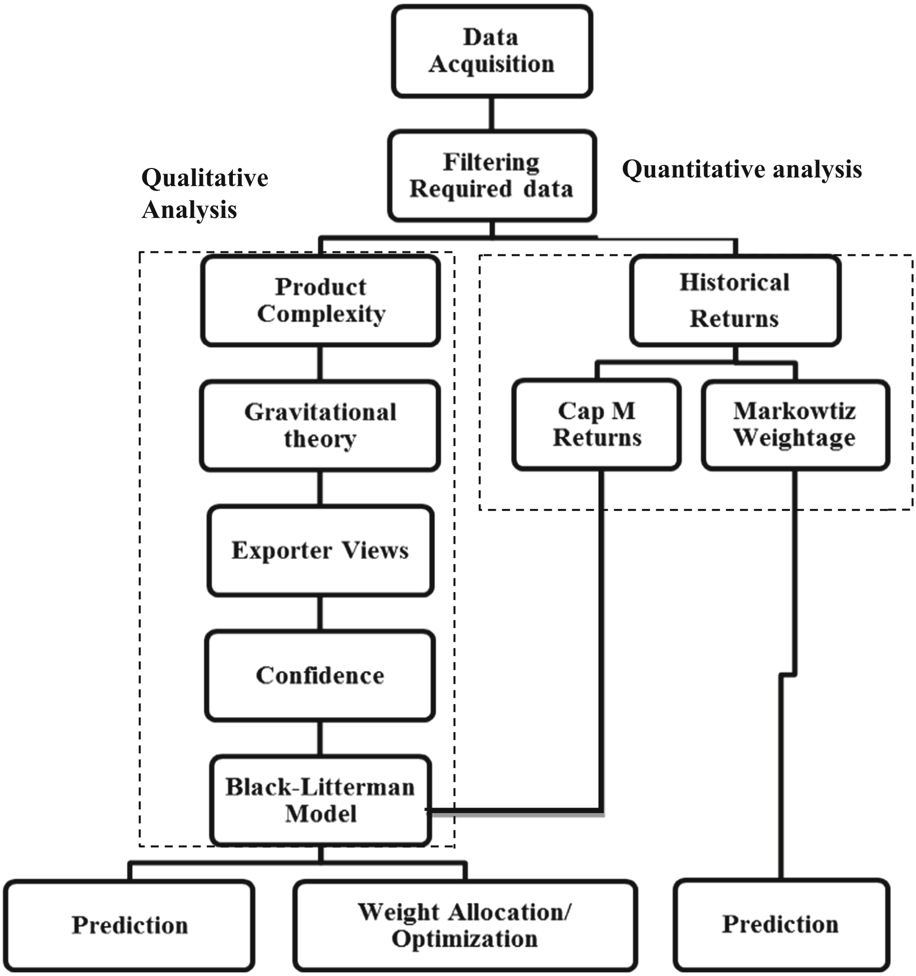

Fig. 3. Proposed algorithm of overall system

$$\sum_{a=1}^{K} X_{c_a} = 1 \tag{4}$$

For several investments amount $a = 1, \ldots, K$ for maximum returns. The expected value or μ(mean) [23] of X defined by Eq. (5) where X be the random variable of finite number value $x_1, x_2, \ldots, x_N$, the probability that $X = x_1$ is and $X = x_2$ is p_2.

$$\mathrm{E} = p_1 x_1 + p_2 x_2 + \ldots + p_N x_N \tag{5}$$

The Variance of X is defined by Eq. (6).

$$V = p_1(x_1 - E)^2 + \ldots + p_N(x_N - E)^2 \tag{6}$$

Where V is the average square deviation of $\sqrt{X}$ from its μ mean, we can calculate standard deviation as $\sigma = \sqrt{V}$ and the coefficient of variation, σ/E. Suppose $Y_1, Y_2, \ldots, Y_N$ are a number of random variables, If Y is the weighted sum of Y_i then,

$$Y = a_1Y_1 + a_1Y_1 + \ldots + a_nY_N \tag{7}$$

$$E(Y) = a_1E(Y_1) + a_2E(Y_2) + \ldots + a_NE(Y_N) \tag{8}$$

Equation (8) is expected value of the weighted sum of random variable, proof 6 for variance; we define co variance σ_{ij} between Y_i & Y_j in Eq. (9).

$$\sigma_{ij} = E\{[Y_i - E(Y_i)][Y_j - E(Y_j)]\} \tag{9}$$

The co-variance between two random variables is equal to the correlation ρ_{ij} times the standard deviation of two variables

$$\sigma ij = \rho ij\sigma i\sigma j \tag{10}$$

Correlation coefficient ρ_{ij} measures the relative co-variance between the commodities returns. The range of ratio is limited by +1.0 and −1.0, ρ_{ij} = +1.0, −1.0 & 0.0 positive, negative and zero Correlation which means at the same span of time returns on two commodities try to move in same direction, opposite direction and independent accordingly. Variance of weighted sum calculated by Eq. (11):

$$V(Y) = \sum_{i=1}^{N} a_i^2 V(W_i) + 2\sum_{i=1}^{N}\sum_{i>1}^{N} a_ia_j\sigma_{ij} \tag{11}$$

We know Y_i is σ_{ii} therefore,

$$V(Y) = \sum_{i=1}^{N}\sum_{j=1}^{N} a_ia_j\sigma_{ij} \tag{12}$$

$$R = \sum RcWc \tag{13}$$

where R_c is the return on the c^{th} commodity. μ_c is the expected return of R_c, σ_{cs} = covariance between R_c & R_s; σ_{cc} = variance of $R_c'W_c$ = percentage weightage of investor of R_c. Similarly, R is the random variable and return on the portfolio is a weighted sum of R & R_c. W_c is the percentage of investment. ${}^{P}W_c = 1$ represent sum of all investment is equal to 1. Therefore, Expected Return & Variance of the portfolio are calculated by Eqs. (14) and (15)

$$E = \sum_{c=1}^{N} W_c \mu_c \tag{14}$$

$$V = \sum_{c=1}^{N} \sum_{s=1}^{N} \sigma_{cs} W_c W_s \tag{15}$$

3.2 Black-Litterman Model

Trade is influenced by the government policies, current trend, gravity model and PCI [20]. Optimal portfolios are very sensitive to inputs, for the small change in input results in a significant change in asset allocation of portfolio. Black-Litterman (BL) introduced an expert view matrix to the Markovitz mean variance optimization and CAPM to add expert's perspective who has experience based information on the assets which are not modelled and are not reflected from the CAPM alone. Return using the BL model is expressed as

$$U = W^T R - \frac{1}{2} A W^T S W \tag{16}$$

Where, A = Risk Aversion; R = Risk; S = Variance Co-Variance matrix; w = weights $\Sigma w = 1$

$$du/dw = R - ASW = 0 \tag{17}$$

Rather, solving for weights, BL argued that weights are already observed in the market therefore they computed them using market capitalization.

$$R = ASW \tag{18}$$

$$A = \frac{E(r_m) - r_f}{\sigma_m^2} \tag{19}$$

$$M = [(\tau S)^{-1} + P^T \Omega P]^{-1} \tag{20}$$

$$E(R) = [(\tau S)^{-1} + P^T \Omega P]^{-1} [(\tau S)^{-1} \Pi + P^T \Omega Q] \tag{21}$$

τ = Scalar number indicating uncertainty usually range (0.025 to 0.05)

$$\Pi = ASW_{mkt} \tag{22}$$

M = Uncertainty of returns; Π = Implied equilibrium returns; P = Investors views matrix; each row a particular view of the market and each element of the row represents the portfolio weights of each asset (K×N matrix); Q = The expected returns of the portfolios from the views depicted in matrix P (K×1 vector); Ω = A diagonal co variance matrix with elements of the uncertainty inside each view (K×K matrix)

$$S_B = S + W \tag{23}$$

S_B = Variance covariance Matrix of Black-Litterman model. Assumed there are N commodities in the portfolio, this formula will calculate new expected return. We used CAP M weights for reverse optimization to include market capitalization factor and an impact of overall trade covariance with each commodity to gain the minimum error in efficient frontier of Black-Litterman model.

3.3 Product Complexity Index

Berkowitz et al. [21], came up with a quantitative measurement of measuring product complexity through PCI. In this method complexity was based on the number of product functions and the level at which they appear in a decomposed function tree. Accordingly, total complexity is measured by (24).

$$C_T = \frac{w_1 C_m + w_2 C_p + w_3 C_{st} + w_4 C_s}{w_1 + w_2 + w_3 + w_4} \tag{24}$$

C_m = f(material, tooling, geometry, process), C_p = f(geometry), C_{st} = f(number of subassemblies, levels in hierarchy, max number of components/sub-assemblies); C_s = f(number of assembly operations), w_t = numerical constraints, where i = 1, 2, 3, 4.

Most of the variable in this measurement are identified by design and production ratings. From the above, the optimum number of components are calculated by (25)

$$\frac{dC_T}{dn} = \frac{d}{dn}\left(\frac{w_1 C_m + w_2 C_p + w_3 C_{st} + w_4 C_s}{w_1 + w_2 + w_3 + w_4}\right) = 0 \tag{25}$$

3.4 Gravitational Model

General Trade Gravity model is expressed as:

$$Y_{IJ} = G\frac{X_I X_J}{D_{IJ}} \tag{26}$$

$$lnY_{IJ} = \alpha_0 + \alpha_1 lnX_I + \alpha_2 lnX_J + \alpha_3 lnD_{IJ} + \in \tag{27}$$

Where ‘I’ and ‘J’ denote the trading nations, X is general is represented by the GDP of the country and D is the distance between the two nations. The conventional Trade Gravity Model proposes that exchange streams between the two nations are emphatically identified with the GDP of the two nations and contrarily identified with the separation between the two nations.

4 Implementation and Results

For implementation, using approach in Fig. 3 various qualitative and quantitative analysis were extracted from the comtrade dataset using the Markowitz portfolio, CAP M. and Black-Litterman model. Each result from the dataset is compared with the actual result to conclude the best model.

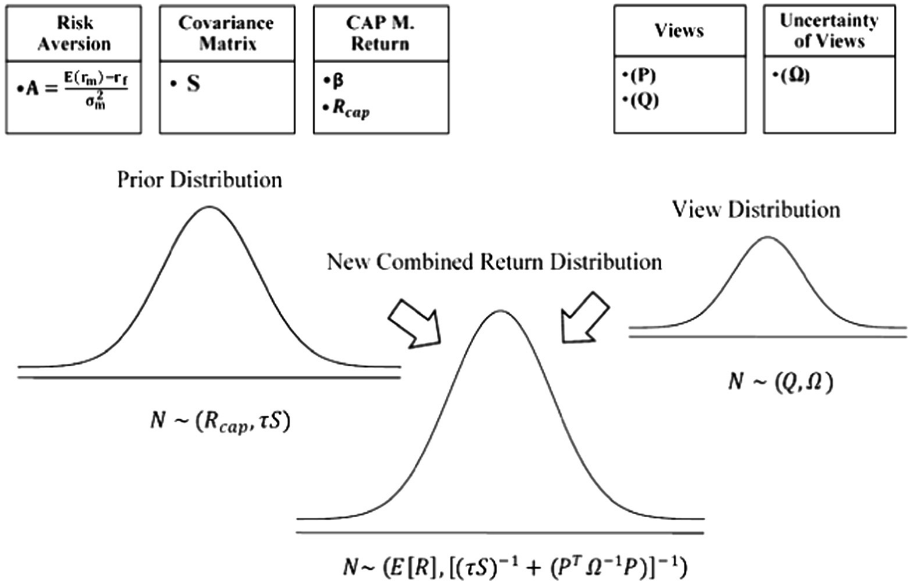

Fig. 4. Prediction approach

4.1 Data Acquisition

HS [6-digit code] dataset of all the commodities from the year 2003 to 2016 was used in this paper. Data of 23 textile commodities was filtered, which were more than 0.5% of the total textile export of Pakistan. The data was acquired from United Nation Commodity Trade Statistics Database [12], their source in Pakistan is Pakistan Bureau of Statistics.

4.2 Qualitative Analysis

Portfolio optimization methods (Markowitz and CAPM) generate risk and return of commodities based on the historical data. Black-Litterman model adds expert opinions and implied equilibrium return to the quantitative methods. We generated implied equilibrium return using CAPM weights. CAPM incorporated the information of the capital pricing and percentage of share of commodity in total export. Expert opinion was derived by the trade specialist who explained the increase or decrease of each commodity by designing a view matrix and giving its corresponding confidence level. The view matrix was obtained on the basis of product complexity index [22], gravitational model [6], government laws, trends [20, 21] and other factors associated with the specific trade. Higher confidence level gives a more assured result of a product. Table 1 Showed each commodity in the view matrix along with its confidence level. Expert showed 0.1% of confidence in commodity 630231 defined as it has the lowest PCI Index of 1.75 and Pakistan is the 3rd largest exporter of this commodity and capturing India's export. Both neighboring countries India and Pakistan share 21% stake of total export but Indian government economic reforms suggesting their transition from labor intensive market to capital intensive has negatively impacted their textile exports as compared to Pakistan. Expert gave negative views on commodity 610590 and 520812. PCI index for 610910 is 1.88 and Pakistan is the top exporter but the main cause of negative views was due to the low demand, continuous decreasing share of total export and negative trend of returns since last 5 year of the acquired data. Commodity 520512 has high PCI index of 2.29 with negative gravitational theory impact. China is the largest exporter with 65% of world total export through Pakistan with share of 12%. Philippines is the top importer with 37% of total world import. Applied gravitational theory results showed China-Philippines impact is 1.1233 billion USD per km and Pakistan Philippines gravitational impact is 0.0145 billion USD per km as the GDP of china is very high and distance is less than Pakistan from Philippines giving China a high advantage in both factors. Similarly, expert defined his views for each commodity with the confidence level based on different factors associated with each commodity. Results showed an exceptional impact on overall forecasting and portfolio optimization by multiplexing the views of expert with past data.

Table 1. View matrix P & confidence matrix Q

Views	Confidence level Q	520512	630260	630231
View 1	0	1	0	0
View 2	0	0	1	0
View 3	0.1	0	0	1

The risk of covariance of each view matrix is shown in the equation. Where Ω is the uncertainty of matrix, S is the covariance and P is the view matrix.

$$\Omega = \tau PSP^T \tag{28}$$

The Covariance matrix S & S_B is shown in Tables 2 and 3.

Table 2. Covariance matrix of covariance S

S Matrix	520512	630260	630231	620322	630239
520512	0.052	-0.010	-0.003	-0.006	-0.019
630260	-0.010	0.017	0.001	0.001	0.019
630231	-0.003	0.001	0.019	-0.017	0.011
620322	-0.006	0.001	-0.017	0.781	-0.013
630239	-0.019	0.019	0.011	-0.013	0.141

Table 3. Covariance matrix of covariance S_B

S_B Matrix	520512	630260	630231	620322	630239
520512	0.038	-0.004	-0.043	0.167	-0.172
630260	-0.003	0.016	0.012	-0.048	0.065
630231	0.001	-0.004	0.029	-0.049	0.037
620322	-0.018	0.004	-0.019	0.986	-0.083
630239	-0.022	0.014	-0.006	0.061	0.073

4.3 Quantitative Analysis Efficient Frontier of Markowitz Model

Using the filtered trade data, calculated expected return from the historical commodities value. Total expected return from the year 2003 to 2016 calculated by Eq. 29.

$$E(R) = \left(\sum_{t=1}^{\tau} \right) \div T \tag{29}$$

Table 4. Expected returns of year 2015 using different portfolio optimization models

S. no.	Commodities	Historic returns	Cap. M returns	BLM returns	Actual return
1	520512	8.17%	−0.08%	−46.88%	−20.34%
2	630260	7.44%	3.41%	41.80%	–5.33%
3	630231	−1.86%	3.12%	−15.63%	3.81%
4	620322	93.07%	3.71%	314.06%	255.38%
5	630239	26.81%	6.95%	10.16%	10.86%

By using Black-Litterman model in Fig. 4, expected returns of 23 textile commodities of Pakistan for the year 2015 using trade data [12] from the year 2003 to 2014, was shown in Table 4. Figures 5, 6 and 7 represent efficient frontier of expected and the actual returns versus risks of the year 2015 using Markowitz, CAPM & Black-Litterman model respectively, indicating minimization of standard error by incorporating expert views using Black-Litterman model. Figure 8 represent the comparative analysis of historical, CAPM and Black Litterman model using mean square error (MSE) metric. Table 5 represents the expected return for the predicted year 2016 of the 23 textile commodities of Pakistan and the weightage allocation for maximum return, minimum variance and maximum sharp ratio. Figure 9 is the efficient frontier graph of 2016 predicted returns versus risks using Black-Litterman model.

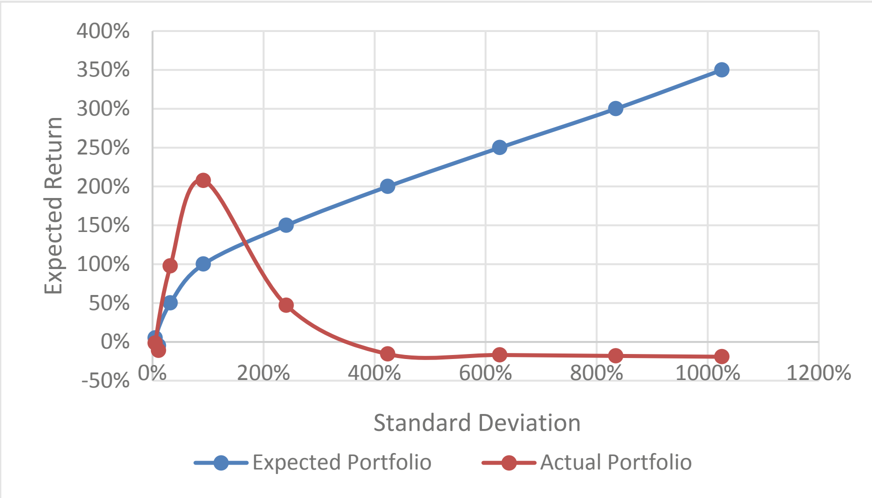

Fig. 5. Efficient frontier of Markowitz model

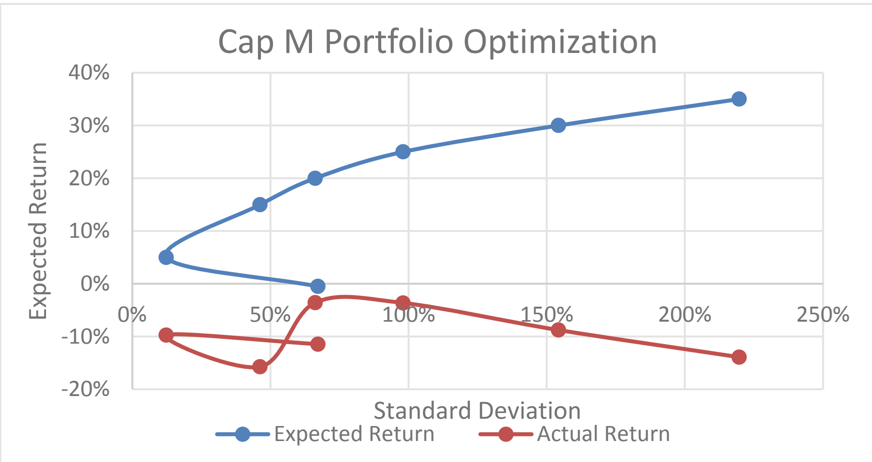

Fig. 6. Efficient frontier of CAP model

Table 5. Expected returns & weightage allocation year 2016 using Black-Litterman model

S. no.	Commodity	Expected return	Weights for max return	Weights for min variance	Weights for max sharp ratio
1	520512	10.67%	0.00%	16.16%	20.24%
2	630260	3.07%	0.00%	24.91%	14.45%
3	630231	−0.61%	0.00%	22.34%	1.60%
4	620322	−19.85%	0.00%	1.54%	0.00%
5	630239	3.47%	0.00%	0.00%	0.00%

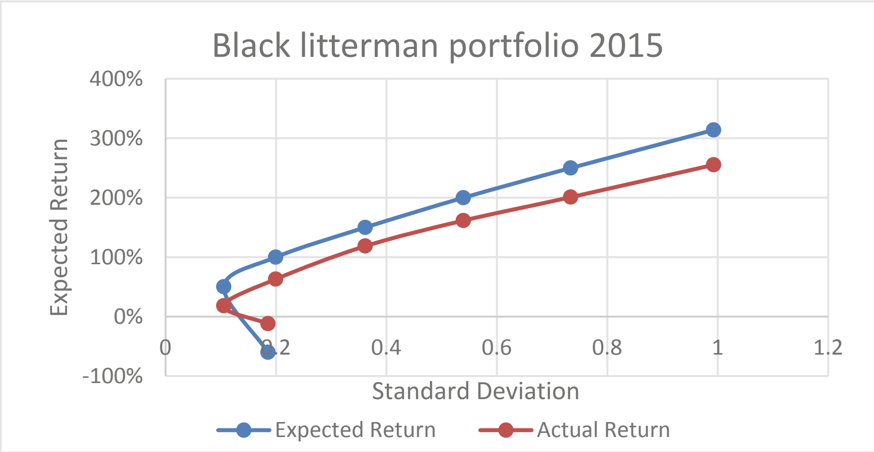

Fig. 7. Efficient frontier of Black-Litterman model

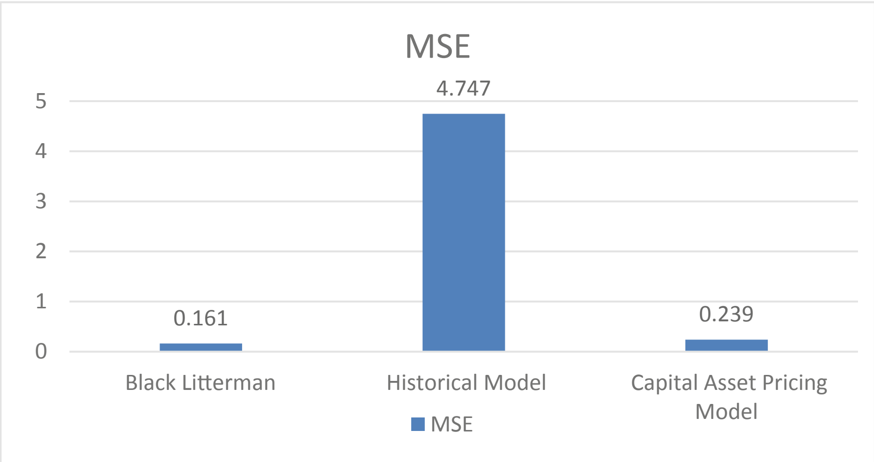

Fig. 8. Comparative analysis of Black-Litterman MSE with Holt & Grey model

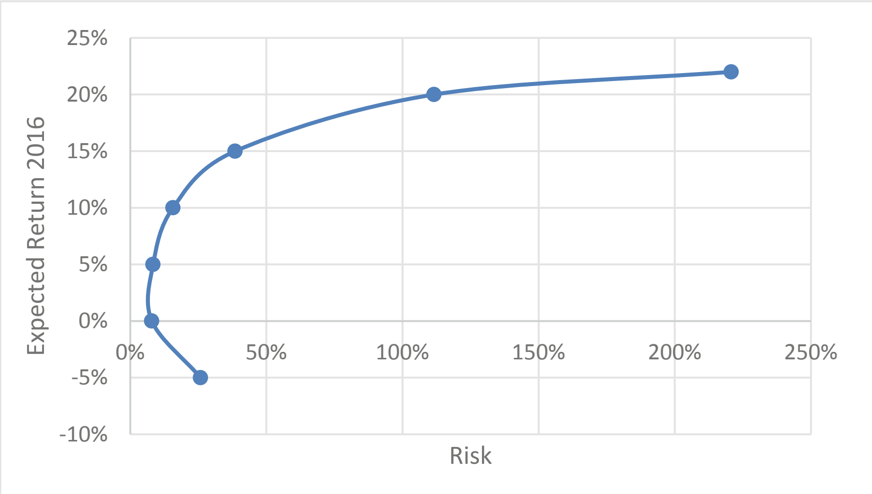

Fig. 9. Efficient frontier for the predicted year 2016 using Black-Litterman model

Comparative analysis of Black-Litterman forecasted with Holt [14] and Grey [17] model showed the Black-Litterman model forecasted better results with risks information of each commodity (i.e. MSE for the specific expected return through Black-Litterman is 0.235 and through Holt and Grey is 1.226 and 1.026 respectively Fig. 12). Figures 10 and 11 showed the predicted and actual textile export of Pakistan using comtrade data from 2007 to 2015.

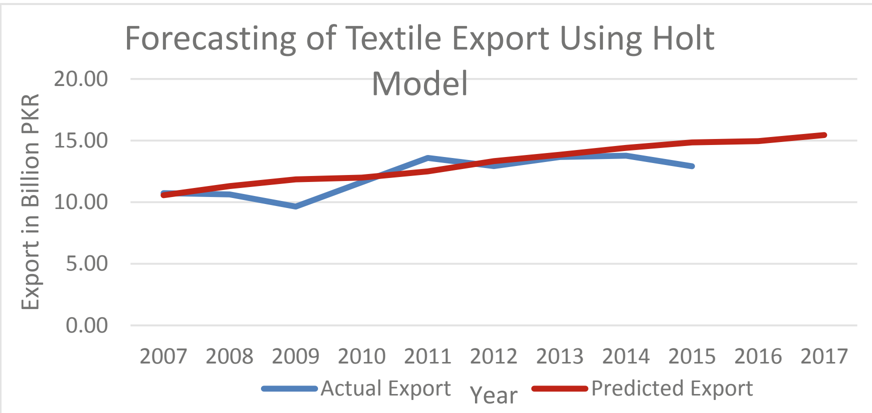

Fig. 10. Forecasting of total textile export using Holt model

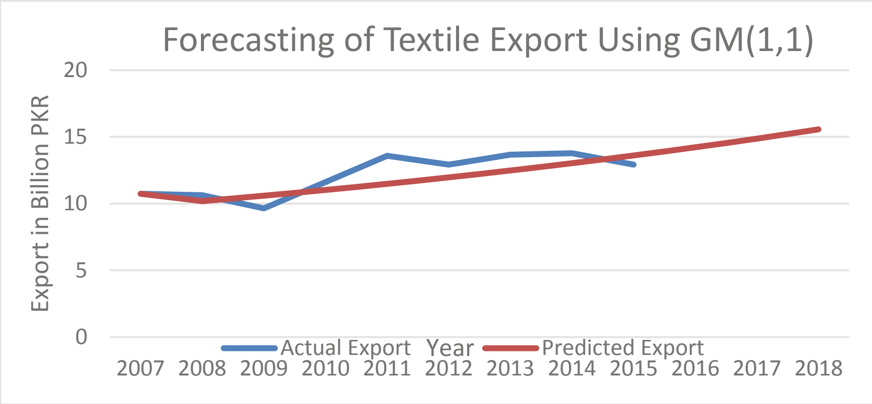

Fig. 11. Forecasting of textile export using Grey model

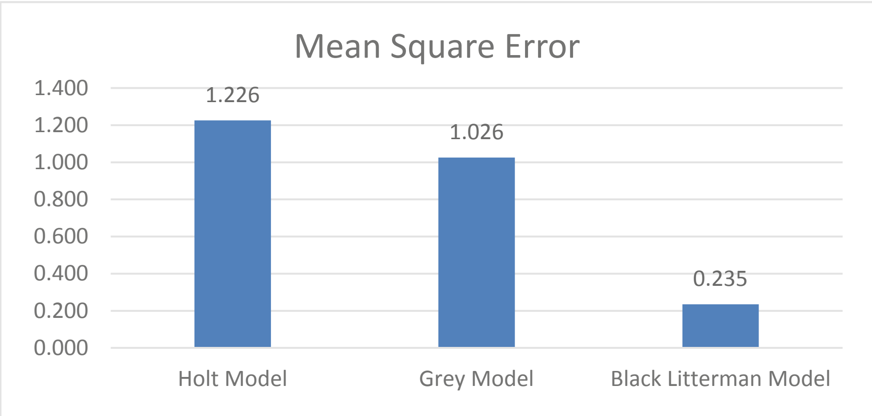

Fig. 12. Comparative analysis of Black-Litterman MSE with Holt & Grey model

5 Conclusion

In this paper, we introduced a portfolio optimization theory which gave the investor control of risks with maximum returns. The risks and returns information was defined for each commodity. The three models, incorporated were Markowitz historical model, CAPM. and Black-Litterman model. As trade data was nonlinear and vary with the overseas demand, expert opinion became crucial for assessment which was utilized by Black-Litterman model.

The efficient frontier of these 3 models using the trade data of the last 13 years was compared. The results indicate that the predicted value of the Black-Litterman model is closest to the actual value and tracks the efficient frontier graph. Later we compared Black-Litterman model with the conventional models Holt and Grey. The results showed Black-Litterman with improved quantitative and qualitative results. We have shown that COMTRADE data can be used in creative ways incorporating proven algorithms from other domains like financial engineering in trade analysis. This paper will inspire further research not only to provide analytics to investors for investment decision making but also for government in formulating their trade policy. In future, deep learning models can be used for prediction of world trade after adding new features representing the classical factors like GDP, freight cost, policy effect etc.

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