Chapter 4

Risk Sources & Risk Awareness in Strategic Sourcing: Indian Automobile Industry Risk Index

4.1 Introduction

This chapter as a sequel to the literature review and the research methodology entails development of the conceptual research framework on risk assessment by constructing a Bayesian belief network (BBN) model, which encompasses all the risk factors relevant to the Indian automotive sector that can give a fair, empirical idea as to how much the risk factors drive down the gross turnover of the industry. Bayesian networks have been considered as they provide a very useful risk assessment tool that takes into account the advantages of both quantitative and qualitative risk assessment methods. The model examines the business, economic and external risks. It evaluates their impact on gross turnover and draws out implications to streamline the risk effects in the Indian automobile industry. It illustrates that the three factors - business risks, economic risks and external risks are not entirely independent and are positively correlated with each other. This chapter contains six sections that are as follows. In the introductory section we present the extracts of relevant literature concerning SSRM focusing specifically more on risk assessment part. In the next section, i.e. Section 2, we explain the research methodology in detail used in development of the Indian automobile industry risk index. In Section 3, we explain the proposed model. In Section 4, we test our proposed model using a case study and present the results with detailed analysis. Section 5 presents analysis of the model developed followed by the conclusion of the proposed method in the last section, i.e. Section 6.

In the past, we have observed supply chain disruptions halting supply chain and affecting economy (Juttner et al., 2003; Hendrisck & Singhal, 2005; Chopra et al., 2012). Further, it has been the pressing need of big companies to address supply chain risk (Craighead et al., 2007). Holton (2004) defined risk "as a situation, having exposure to an event and event has possibility of uncertain outcomes". Concept of risk has many facets and is discussed at length in different fields of study like insurance, finance, clinical research, etc. Discussion of risk in supply network literature is relatively a new concept. Managing supply risk can be a challenging task due in part to the complex and dynamic nature of supply networks. Supply

Paper under publication in International Journal of Logistics System and Management, forthcoming (DOI: 10.1504/IJLSM.2019.10011817); accepted on 20 April 2018

networks are dynamic and can manifest themselves uncertainty existing in demand requirements, capacity, delivery time, manufacturing costs (Mathiyalakan, 2006). Paulson et. al. (2011) identified 15 risk factors out of which 12 have 'expected result impact' and three have 'known result impact'. Kull and Talluri (2008) defined risk in supply chain in association with goal achievement. They identified various risks that cause deviation in the supply network goals like delivery, cost, quality, flexibility and confidence. Business efficiency, stakeholder pressure and the need for legislative compliance compel the automotive sector to design and manufacture fuel-efficient, low-impact, environmentally responsible and sustainable vehicles. Managing and responding to these multiple and sometimes conflicting interests necessitates the measurement of economic, environmental and societal performance (Jasiński et al., 2016).

Pandey and Sharma (2017) analysed various risks which may disrupt the automotive supply network. Authors identified 17 potential modes of failures or risk sources through close scrutiny of literature and weighted risk priority numbers (WRPN) have been calculated. Aghapour et al., 2017 empirically investigated the sequential impact of this managerial process on non-financial performance of three execution decision areas of the SCOR model. Data was collected from 160 high level managers with knowledge of past and present organizational practices. Using partial least squares modelling (PLS-SEM), analysis of manufacturing plants from six industries indicates that superior risk identification supports the subsequent risk assessment and this in turn leads to better risk mitigation. Garvey, et al. (2015) utilized a Bayesian network (BN) approach and developed a model of risk propagation in a supply network. The model takes into account the inter-dependencies among different risks, as well as the idiosyncrasies of a supply chain network structure. Specific risk measures are derived from this model and a simulation study is utilized to illustrate how these measures can be used in a supply network setting. Supply chain risk literature highlights the importance of risk assessment. Different authors like Gardens and Borghesi (2008) used analytic hierarchy process (AHP) method. Webber et al. (2012) proposed Bayesian network methodology where number of risk factors are limited. There has not been much research in the literature on sourcing/ supply network risk assessment. Most of the research papers address the complete supply network risk assessment, whereas they lack in providing a comprehensive supply chain assessment tool because of its complexity.

In many industries risk management is still thought to be primarily a company-specific goal as Jüttner (2005) points it out: "Companies implement organization - specific risk management, but there is little evidence of risk management at the supply network level". The ripple effects of supply chain disruptions are also reflected in the company's stock price and its financial statements. Hendricks and Singhal (2005) investigated the effects of supply disruptions on stock prices and capital investment risks. They concluded that the firms take a lot of time to rectify the negative effects of disruptions. No company wants disruptions in their supply network operations. The utmost priority of companies is business continuity and customer satisfaction (Wei et al., 2018).

We know that one of the main factors which contribute to a supply network's stability and consistency are the raw materials which the company acquire in order to develop their product. Christopher and Matthias (2011) worked on a supply chain volatility index and showed how the current sourcing/ supply network management practices may no longer fit the environment that most of the companies operate in nowadays. They argue that after 2009, the companies are not just exposed to a temporary shock that will quickly pass, but there is much volatility in the market that will lead to higher variance in vital business factors: from energy cost, to raw materials, and currency exchange rates. They concluded that the current foundations of the sourcing/ supply networks were built on the basis of the low price of a single commodity such as oil, or low labour cost and that a new system should be explored to overhaul the supply chain foundations. Das and Nayak (2017) studied the rice supply chain in India and discussed various supply chain risk factors like logistical problems, on time delivery, opportunistic behaviour, product specification, average lateness, on time governance mechanism, reduction in cost, degree of inconsistency, increase in knowledge flow between firms and climate change on agricultural ecosystems, which have been a matter of concern for food security in the present situation.

One of the newer methods which include both quantitative data and subjective expert opinions is the Bayesian network modelling approach. Lockamy and McCormack (2012) explored a new method using Bayesian networks for determining a supplier's overall risk probability, and the probable impact a supplier can have on the cash flows of the company. They concluded that the supplier risk profiles can be used to identify and single out risk events which have the largest potential influence on a company's cash flows. Sharma and Saurabh (2015) evaluated supply chain risks using Bayesian belief network modelling. One of the limitation of their model is presenting the risk variables in binary form and not including many significant risk factors in sourcing/ supply networks.

More recent work on Bayesian network modelling has been done to study the information risk flow in Indian automotive companies. Sharma and Routroy (2014) presented a causal relationship among various information risks in a supply chain, namely, information security, information leakages and reluctance toward information sharing using a quantitative Bayesian network modelling. The three factors were shown to be having a major influence on a company's revenue.

The literature review in Chapter 2 contains a good amount of research material dealing with SSRM, it clearly shows that there is a lot of work that can be done to model sourcing/ supply risks using financial ratios and standard proxy variables from firms' financial statements (Lixandru, 2016). The link between the raw material market indices, various liquidity ratios and quantitative analysis of business and credit risk can be used to identify and state possible solutions for a company's sourcing/ supply risks. Another solution would be to use a Bayesian network model when taking into account various subjective factors which cannot be quantified, and has a lot of scope in analyzing sourcing/ supply risks. A huge step in analyzing supply chain networks has already been undertaken by Lockamy and McCormack (2012) using Bayesian network modelling. There is still a gap existing in the area of integrating the reviewed methods in the whole industry perspective. This chapter tries to integrate all the factors into a generalized Bayesian Network model. Different researchers have provided the conceptual and empirical studies on sourcing/ supply risk management. In recent past, some of studies developed BBN model, but all of these lack in terms of comprehensiveness in one industry specific sourcing/ supply network risk factor. In this research we would be combining relevant aspects summarized above and hope to provide an empirical model to assess and evaluate industry specific risk which would include financial risks, economic risks, supply network and natural calamities risks.

4.2 Research Methodology

Various methods to analyze the supply disruptions, financial risks and economic - both macro and micro risks has been discussed in literature review section. Fundamentally two different views have evolved over the years on how risk should be assessed. The first view is known as objectivist, or frequentist. This approach requires probabilities, which are obtained from repetitive historical data, and it is based on probabilistic risk assessment (PRA). Another view is Bayesian network modelling, which is based on Bayes' theorem and PRA concepts. Bayesian view considers the expert judgment as a part of risk assessment. A Bayesian takes not only data into account but also experts' judgment about the situation.

Consequences are expressed with numbers and their chances of occurrence are expressed as probabilities or frequencies. The total risk is the expected loss: is the summation of consequences multiplied by their probabilities (Ramana, 2011). Bayesian networks are more often used to analyze causal relationships between entities. In the business field, Bayesian networks are a useful tool for a multi-variable analysis of the risks, for the ongoing monitoring and for the evaluation of strategies to mitigate such risks by decision and tornado graphs (Jensen, 2001; Alexander, 2003). To estimate the frequency and the impact distributions of risky events, historical data as well as experts' opinions are typically used (Cruz, 2004). In this context, Bayesian networks are a useful tool to integrate historical data with the opinions from experts, which can be qualitative or quantitative (Fanoni, Giudici, and Muratori, 2005). We have tried to integrate both the methods into a generalized Bayesian network method. Thus, Bayesian networks suited all the requirements including the data unavailability in India that we had for risk assessment in Indian automotive sector. The following subsection provides a brief overview of Bayesian networks.

4.2.1 Bayesian Networks

In probability theory, where conditional probabilities are concerned, Bayes' rule plays a central role. It is stated mathematically as:

$$P(A \mid B) = \frac{P(B \mid A)\, P(A)}{P(B)}$$

Where A and B are events and $P(B) \neq 0$.

- P(A) and P(B) are the probabilities of events A and B occurring independent of each other.
- P(A | B) is the probability of event A happening given that B has occurred.
- P(B | A) is the probability of event B occurring given that A has occurred.

In other words, this means that the posterior probability in a hypothesis A after observation of some evidence B is equal to the likelihood of observing B given A , times the prior probability of A , divided by the prior probability of B.

Now coming to Bayesian networks, it can be seen as some form of an expert system. Belonging to the field of artificial intelligence, an expert system is a computer program that holds knowledge in some domain and is able to use this knowledge to perform tasks that a human expert normally would perform. A Bayesian network (BN) is a directional non-cyclic graph consisting of nodes which correspond to a set of random variables and arcs. The directional arcs (or links) connect the nodes, representing the interdependences between variables.

Assuming discrete variables, the strength of the influence between the parent nodes or variables is shown by conditional probability distribution tables associated with each node. The only limitation on the arcs in a Bayesian network model is that there must not be a closed cycle. The next section, step by step methodology for BBN modeling is provided.

4.2.2 Bayesian Belief Network Modelling Steps

The implementation of Bayesian belief networks (BBN) modelling requires risk factor identification and then establishing relationship between them. The initial stage in the BBN model development is Structural Development and Evaluation, which on the first iteration will produce an unparameterised causal network. This phase of model development can be undertaken via a knowledge or data-based approach. Knowledge based model development is done through expert elicitation of parameters. The supply risk factors were identified using literature review and then prepared list was sent to experts for validation. Once relevant variables were identified, then experts were asked to draw linkages between various risk factors, used in the study.

Delphi method was used for establishing structural relationship among variables and subsequently assigning weights to the Indian automobile industry's risk source elements/ components thereof. Once, opinions of experts converged on a particular structure, it was further evaluated. The experts were IT managers and supply chain managers. In step 3, prior to parameterisation, all variables were discretised into states. For continuous variables, states were further discretised into sub-ranges. Wherever possible, states were established using recognized classifications, management thresholds or guidelines. Where, these guidelines were not available, sub-ranges were specified with the guidance of the experts. The number of 'states' or 'classes' assigned to each variable were not pre-determined, but evaluated and assigned on an individual basis. In step 4, expert elicitation is applied to the whole conditional probability tables (CPT), rather than individual parameters. For parent nodes, priors were elicited and for child nodes, CPT was elicited for each possible state for particular child node.

In this study, guidance for elicitation was sought from Morgan and Henrion (1990). In the last step, "Sensitivity Analysis" is used to measure the sensitivity of changes in probabilities of query nodes (output variables) when parameters and inputs are changed. The query nodes in this study were model endpoints. Two types of sensitivity analyses were used in evaluating the BBN. The first, ''sensitivity to findings'', considers how the BN's posterior distributions change under different conditions, while the second, ''sensitivity to parameters'', considers how the BN's posterior distributions change when parameters are altered (Chin et al., 2017). In the next section a brief overview of BBN modelling has been provided.

4.3 Risk Factors for Automotive Industry

In this section, we provide detailed model development process for risk assessment in automotive industry. BBN modelling process starts with risk factor identification. As discussed, we extracted several factors from the literature review that are believed to affect the amount of risks present in the automotive industry. A total of nine risk factors, namely Demand volatility, Inadequate R & D expenditure, Credit risk, Exchange rate fluctuation risk, Raw material price fluctuation, Supply chain disruption, Regulatory risk, Economic instability and Country risk, have been identified from the literature and details including their description and references have been given in Table 2.4, as part of literature review chapter. Their inclusion in the evolved model has been defended through expert opinion.

4.3.1 Data Collection Procedure

The data for the factors which were quantifiable were taken from various sources. A brief overview of the data sources for each factor outlined above is given below. The companies - two domestic and two MNCs - which we are taking as a proxy for the Indian automotive industry are:

- Tata Motors.
- Mahindra & Mahindra.
- Toyota.
- Hyundai Motors.

Following part presents the brief discussion on the data collection with their sources for all the variables used in this research study.

4.3.1.1 Demand Volatility

The demand volatility data is mainly taken from the net unit sales of the industry during a period from 2006 to 2015. The data for the total industry sales has been taken from the open Government data (OGD) platform provided by Government of India (GoI). The sales include both the passenger vehicles as well as commercial vehicles sales.

4.3.1.2 Inadequate R&D Expenditure

In view of the intense competition and shorter product development cycle in automobile industry, innovations and R&D are key focus areas. Inadequate R&D expenditure poses risk to companies operating in this industry. The data for the R&D expenditure has been taken entirely from annual reports of the four companies and the Capitaline Database, a digital corporate database of Indian companies with structured and systematic presentation of financial data making corporate analysis easy. The expenditure costs include only the research and development costs incurred by the companies.

4.3.1.3 Credit Risk

The credit risk ratings for the four companies are taken from the Moody's ratings from their website. We only have a ratings description for the ratings published by Moody's. To quantify this data, an article on Seeking Alpha, a crowd-sourced content service for financial markets wherein, the author of the article, Dividend Drive (2016) proposed a way to quantify the rather subjective ratings given by the ratings agencies. The ratings were then converted to numbers and grouped by year to get a general idea for the credit ratings of the debt owed by the four companies.

4.3.1.4 Exchange Rate Fluctuation Risk

Exchange rate fluctuation, especially in the developing countries, like India, pose a significant risk. Based on the annual reports and the 20-F SEC filings by the companies, we narrowed down the list of foreign currencies too, which the Indian Rupee is the most exposed in context with the automobile industry. The foreign currencies include:

- U.S. Dollar.
- Pound Sterling.
- Euro.
- Japanese Yen.
- Australian Dollar.
- South African Rand.
- Singapore Dollar.
- Chinese Yuan.
- Russian Ruble.

The data has largely been taken from the OFX group site, as the data there is free and accessible, embedded in tables, so it's easy to use it for the analysis.

4.3.1.5 Raw Material Price Fluctuation

Fluctuation of the raw material price has a significant impact on the profitability of the manufacturing company, especially in the Indian automobile sector. The data for the raw material which include steel, aluminum, rubber, glass, plastics, copper and zinc. Futures contracts prices were used for this factor as the automotive industry companies generally do not engage in the spot market where the prices are very volatile. So to hedge their price volatility risk, they participate in futures and forward contracts. The data has been taken from the Index Mundi website (commodities section) and Investing.com website.

4.3.1.6 Supply Chain Disruptions

Supply chain risks and disruptions data is not usually public, although some of the subjective matter is found in the companies' annual reports. The data for this factor was collected through a questionnaire which was circulated to twenty one supply chain managers in different automobile companies in India. The data was collected in the discrete form, with three classes - High, Medium, Low risk.

4.3.1.7 Regulatory Risk

The data for the taxes and duties has been entirely taken from the Capitaline Database for a period of eight years from 2007 to 2015. The legal risk data cannot be generalized for the industry through data for different companies. Hence, we used a question from the questionnaire presented to 21 different managers to quantify it. The data was in the form of three classes - High, Medium, Low risk.

4.3.1.8 Economic Instability

The sub factors included in this factor are GDP growth rate, GNI per capita and the IIP - Index of Industrial Production. The data for GDP and GNI per capita were taken from the World Bank data bank. The IIP index data has been taken from the OGD - platform provided the GoI.

4.3.1.9 Country Risk

As we already discussed above, country risk is the result of political, social and economic factors. The data for the historical country risk for the above different countries has been taken from the OECD - Organization for Economic Co-operation and Development platform where the Country Risk Assessment Model group publishes its country risk score for all the countries.

4.3.2 Discretization of Continuous Data

The data we collected from different sources is in the form of time series data or continuous data. The expert opinion data is in the form of discrete data in terms of three classes or intervals - High, Medium, Low. To simplify our Bayesian network model, we decided to convert every continuous piece of data into discrete data classifying them into 3 states - High, Medium, and Low. The reason behind discretization of all data was to make the Bayesian model a little simpler and have homogeneous data across the nodes in Bayesian belief network. An 'R' script was used to classify the data into three different states based on equal interval width and then counting the frequency of data in each class.

The R script looks like this:

```
library(arules)
setwd("C:/Users/vishad/Desktop/Thesis/")
gross_units = read.csv("gross_units.csv")
gross_units_df = gross_units[,2]

d = discretize(gross_units_df, "interval", categories=3)

# [2065234,2735224) [2735224,3405215) [3405215,4075205]
d
```

Let us explain how this code works.

There is a package available for R called 'arules'. This R package includes certain methods for presenting, manipulating and analyzing transaction data and patterns.

So we set our working directory to the path where our data files are stored. The data files are separate for each factor and parameter and stored in a .csv file. The .csv file contains two columns - one for the date/month/year and the other the corresponding value of the factor.

The next step in discretizing the continuous data is to strip the date column and keep only the data column. Using a function 'discretize' already present in the 'arules' package, which converts a continuous variable into a categorical variable based on the type of discretization method you select. Available are: "interval" (equal interval width), "frequency" (equal frequency), "cluster" (k-means clustering) and "fixed" (categories specifies interval boundaries). This function basically utilizes unsupervised methods to convert continuous variables into a categorical or discrete variables suitable for further analysis.

We chose to use the interval method which sorts the data into equal interval width classes. We set the categories parameter to 3 as we want the data to be sorted into 3 states - High, Medium and Low.

After running the discretize function, an output similar to given below is obtained:

```
Levels: [2065234, 2735224) [2735224, 3405215) [3405215, 4075205]
```

So we have the upper and lower boundaries for each state. Now we need to classify each data point into the discrete states and count the number of data points in each state (frequency). For this, we would need to use an 'IF' query in Microsoft Excel.

For most of the data points, the following sample query format would be applicable:

```
=IF(AND($BG2>=5.2,$BG2<7.22),"L",IF(AND($BG2>=7.22,$BG2<9.23),"M",IF(AND($BG2>=9.23,$BG2<=11.26),"H",0)))
```

Some data points like, R&D expenditure risk, Credit risk, GDP risk, GNI per capita risk, and IIP - Index of Industrial Production risk data, the query needs to be tweaked a little to:

```
=IF(AND(B$2>=3.9,B$2<6.03),"H",IF(AND(B$2>=6.03,B$2<8.17),"M",IF(AND(B$2>=8.17,B$2<=10.4),"L",0)))
```

This has to be done as the risk for these variables is high if the value of these parameters is low, whereas for other variables like exchange rate risk, country risk, raw material price risk, the risk is high, if the value is high.

Paper under publication in International Journal of Logistics System and Management, forthcoming (DOI: 10.1504/IJLSM.2019.10011817); accepted on 20 April 2018

So, after implementing the above method for all data points, the discrete data classes for all variables would be perfect for running BBN model.

4.4. Model Development

This research employs a risk assessment model for quantifying supply risks in a supply chain. The model consists of the nine risk factors: Demand Volatility, R & D Expenditure, Credit Risk, Exchange Rate Risk, Raw Material Price, Supply Chain Disruption, Regulatory Risk, Economic Instability, Country Risk. For risk factors identification, five senior level managers in supply chain/ sourcing domain were invited to participate in an expert opinion survey and based on their feedback, the following model structure has been proposed. As described in the research methodology section, BBN modelling requires the prescription on number of states of all the variables included in the model. Considering a large number of variables (nine) and their sub factors, we have chosen intermediate level of risk factors as Business risk, Economic risk and External risk. Model in Fig. 4.1 presents a compact model for automotive supply risk assessment. In this model we have taken only three major risk factors. Further, through Figs. 4.2, 4.3, and 4.4, the sub risk factors under the head of major risk factors have been shown. The output variable in the model is effect on turnover of the industry. The effect on the net turnover of the industry is calculated by a simple parameter: change or growth rate of the gross turnover of the industry. The data for this has been collected from society of Indian automobile manufactures (SIAM) reports, which are released annually. This node is outcome variable in the model. We would enter the prior probabilities of all the parent nodes of this child node, which is target node for the analysis.

Each node represents a risk factor and direction of the arrow signifies the relationship between them. The following diagram showing structural relationship is also known as influence diagram. To construct our Bayesian network model, we used a software called GeNIe. GeNIe is the graphical interface to SMILE, a 'Bayesian inference engine' developed by the Decision Systems Laboratory. It is a versatile and user-friendly development environment for making Bayesian network models using different algorithms available.
Our general Bayesian model after careful literature review is as follows:

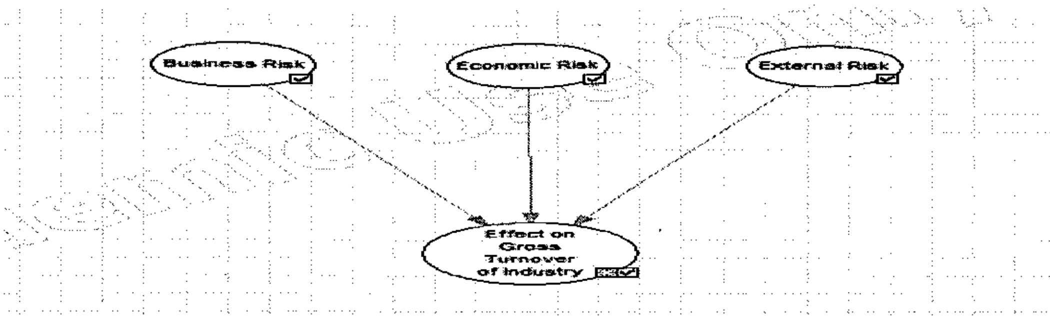

Fig. 4.1: Bayesian model for Automobile Industry Risk

Source: Singh et al. (2018)

For the simplicity of the presentation of the model, we have presented the sub models for all the three main risk factors viz. Business risk, Economic risk and External risk in different subsections.

4.4.1 Business Risk

Business risk consists of three risk variables - Inadequate R&D expenditure risk, Credit risk and Demand volatility risk. All these three variables represent business risk. Now to calculate the prior probability for business risk, we need to determine how much weight does each variable have on business risk.

The flow chart for business risk is given in fig 4.2.

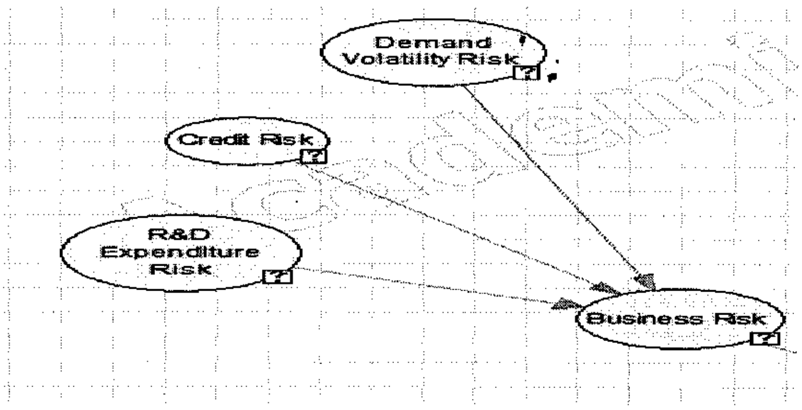

Fig. 4.2: Business Risk Model

Source: Singh et al. (2018)

Weights of the sub risk factors identified after careful examination of the literature and in discussion with the experts in the industry have been assigned through Delphi method.

The weight for Inadequate R&D expenditure is set to 25%. Although India is on the road to becoming one of the major R&D hubs for automobile companies, other than the domestic automotive manufacturers, most of the companies still have their R&D centers outside India (Hindu Business Line, 2014).

For the credit risk, we can see that all the four companies are fairly profitable and hence mostly clear from credit risk. There is still a concern for the companies looking to lease credit lines from the banks, as the credit outlook for the Indian automobile manufacturers has not always been good (Chandan, 2017). Still, they are a low and medium risk for the industry (Shah, Sinha, 2013). It has been assigned a weight of 35%.

Demand volatility is one of the major risk factors affecting the cash flows of the automobile industry in India. As this factor is directly responsible for the number of sales, it has been assigned a somewhat higher weight of 40%.

4.4.2 Economic Risk

Three variables constitute a major part of the economic risk factor – economic stability risk, exchange rate fluctuation risk, and country risk.

The flow chart for economic risk looks like:

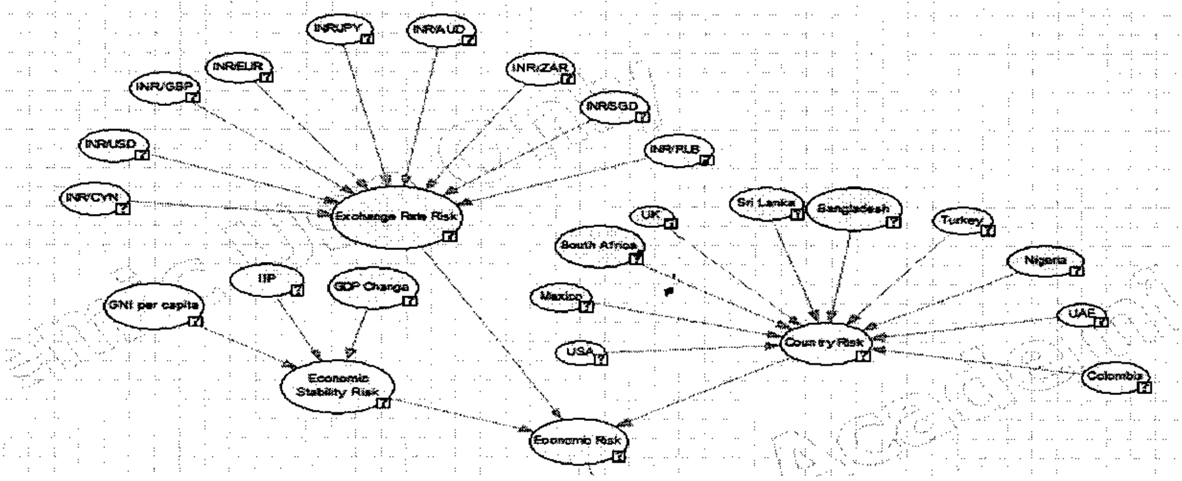

Fig. 4.3: Economic Risk Model

Source: Singh et al. (2018)

4.4.2.1 Economic Stability Risk

The economic stability risk can be sub-divided into 3 more factors - GDP growth risk, GNI per capita risk and IIP change risk.

As we can clearly see from a macro-economic point of view, all these sub-factors are directly correlated with each other and each sub-factor has been assigned a weight of (1/3).

The weight of the economic stability factor, one of the major factor affecting industrial production, labour employment and thus, sales as a whole for the economic risk, has been assigned as 30%.

4.4.2.2 Exchange Rate Fluctuation Risk

The estimated weights of the affected currencies, constituting exchange rate fluctuation risk, have been arrived at by the Delphi method for arriving at conserves amongst experts/ explained in section 4.2.2. Much of the raw material import, mainly rare earth metals, comes from China, Australia and Russia (ASPA, 2017). Hence the Yuan, Australian Dollar and the Ruble have been assigned weights 15%, 15% and 15% respectively. The next level of imports, historically, have been from Japan (Yen), Europe (Euro) and South Africa (Rand). They have been assigned an estimated weight of 12%, 12% and 9% respectively. Automobile companies import lesser amount of raw materials from highly developed nations like the USA (US Dollar), the UK (Pound Sterling) and Singapore (Singapore Dollar). But the technology and some of the finished components are imported majorly from these countries. They have been assigned a weight of 8%, 8%, and 6% respectively.

The exchange rate risk factor is one of the major variables in the calculation of economic risk and it has been assigned an estimated weight of 40%.

4.4.2.3 Country Risk

The weights for the country risk are allotted using a simple method. As we discussed above, the top ten export destinations for automobile companies in India are given in Table 4.1.

Table 4.1: Weights for the Country Risk

Rank	Country	Value (US$)	Share	Weight
1	United States	1.2 billion	8.40%	0.18
2	Mexico	$1 billion	6.90%	0.14
3	South Africa	$888.8 million	6.10%	0.13
4	United Kingdom	$637.4 million	4.40%	0.09
5	Sri Lanka	$596.9 million	4.10%	0.09
6	Bangladesh	$592.1 million	4.10%	0.09
7	Turkey	$580.4 million	4.00%	0.08
8	Nigeria	$546.8 million	3.80%	0.08
9	United Arab Emirates	$433.6 million	3.00%	0.06
10	Colombia	$428.9 million	3.00%	0.06
			47.80%	

The total share of exports for these 10 countries is 47.8% as we can see from the Table 4.1. So to assign these weights, we normalized each value of 'Share' column with respect to the total percentage of exports, which is 47.80% in order to get the weights for each of the countries.

The net weight of the country risk factor has been assigned 30%.

4.4.3 External Risk

Three variables constitute a major part of the economic risk factor – raw material price risk, regulatory risk, and supply chain disruption risk.

The flow chart for external risk looks like:

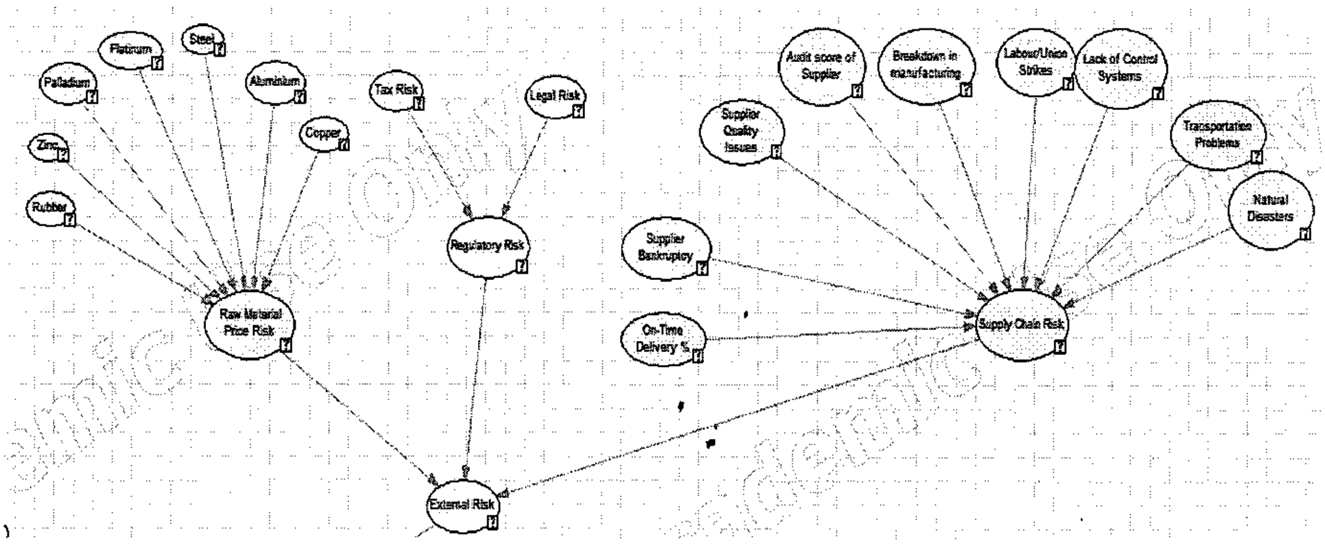

Fig. 4.4: External Risk Model

Source: Singh et al. (2018)

4.4.3.1 Raw Material Price Fluctuation Risk

The major raw materials used in the automobile industry are - steel, aluminum, rubber, platinum, palladium, copper and zinc. Weights to the raw material futures contracts prices as follows.

Steel, aluminum and rubber are allotted the more heavy weights namely, 20% each (Kallstrom, 2015). Palladium and platinum are allotted 15% each, as rare earth metals are used very frequently in automobiles (Aspa, 2017). Zinc and copper are not used as much in their raw form, so they are assigned smaller weights of 5% each. The overall weight allotted for the raw material price risk factor is 35%.

4.4.3.2 Regulatory Risk

Any industry or sector in India has a high exposure to legal fees and tax duties. Various types of taxes such as sales tax, excise duty, import duty etc., are levied upon by the government which cuts down the profitable income of the industry. Legal fees are seldom required when the company runs into disputes with their suppliers or distributors. But when disputes occur, and they occur frequently, the costs are very high. Equal weights of 50% each to both tax risk and legal risk have been assigned. The overall weight allotted for the regulatory risk is 15%.

4.4.3.3 Supply Chain Disruption Risk

We already outlined that the data for the supply chain risk factors has been collected through a questionnaire. All the questions in the survey, are equally important and pose an equal risk to the supply chain network, so all the nine factors have been assigned an equal weight of (1/9). The overall weight allotted for the supply chain disruption risk is 50%.

In the next section, we analyze the data and the output given by the GeNIe software. We would also perform sensitivity analysis for the model and defend the reasons using appropriate arguments.

4.5 Model Analysis

The data was collected and feed into GeNIe software. After calculation of all the prior probabilities of all the respective nodes, shown in sub-models 2, 3 and 4, the final probabilities for the parent nodes are given in Table 4.2 below.

Table 4.2: Probabilities of Main Risk Factors and Outcome Factor

Risk Factors	High	Medium	Low
Business Risks	0.33591903	0.25947104	0.40460993
Economic Risks	0.288261145	0.350506984	0.361231871
External Risks	0.280427848	0.360635578	0.358936574
Effect on Gross Turnover of the Industry	0.162727273	0.633636364	0.213636364

The resulting model with the values computed by GeNIe looks like this:

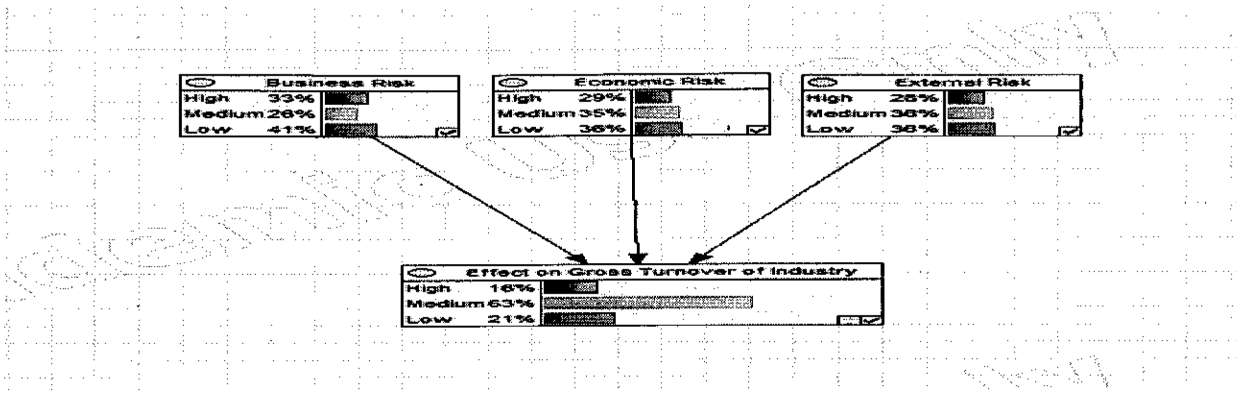

Fig. 4.5: Probabilities of Major Risk Factors and Outcome Factor

Source: Singh et al. (2018)

Here, we have used discrete variables and three states (High, Medium and Low) for each discrete variable to keep the computation simple. This model presented in Fig. 4.2 contains four variables or nodes. There are three parent nodes, that are the nodes with no predecessors and one child node (with only predecessor node(s)) that is effect on industry turnover. We entered the prior probabilities for the parent nodes as definitions and for the one child node, virtual evidence as calculated using data collected using software. When the specified outcome of each node and their probability values are set in the model, the belief network is ready to be updated. The belief update allows us to perform Bayesian inference. The software calculated the posterior probabilities for all the parent nodes and the child node. We will analyze the effects and explain the posterior probability of the target node.

Business Risk	High								
Economic Risk	High			Medium			Low		
External Risk	High	Medium	Low	High	Medium	Low	High	Medium	Low
High	0.25	0.25	0.22222222	0.25	0.25	0.22222222	0.22222222	0.22222222	0.16666667
Medium	0.5	0.5	0.55555556	0.5	0.5	0.55555556	0.55555556	0.55555556	0.66666667
Low	0.25	0.25	0.22222222	0.25	0.25	0.22222222	0.22222222	0.22222222	0.16666667

Medium								
High			Medium			Low		
High	Medium	Low	High	Medium	Low	High	Medium	Low
0.25	0.25	0.22222222	0.25	0.25	0.22222222	0.22222222	0.22222222	0.16666667
0.5	0.5	0.55555556	0.5	0.5	0.55555556	0.55555556	0.55555556	0.66666667
0.25	0.25	0.22222222	0.25	0.25	0.22222222	0.22222222	0.22222222	0.16666667

Low								
High			Medium			Low		
High	Medium	Low	High	Medium	Low	High	Medium	Low
0.22222222	0.22222222	0.16666667	0.22222222	0.22222222	0.16666667	0.16666667	0.16666667	0
0.55555556	0.55555556	0.66666667	0.55555556	0.55555556	0.66666667	0.66666667	0.66666667	1
0.22222222	0.22222222	0.16666667	0.22222222	0.22222222	0.16666667	0.16666667	0.16666667	0

Fig. 4.6: The Posterior Probability for the Target Node

Source: Singh et al. (2018)

Following are some of the key observations from the Bayesian Belief Network model analysis:

- The probability that the risk on the gross turnover is high or low when there is high business, economic and external risks is 25% which is moderate.
- The probability that the risk on the gross turnover is medium/ moderate is the highest for all scenarios, whenever one of the business, economic or the external risk is low, one of the three may be affecting the costs little more than others.
- We can safely conclude that the probability of high risk for all or each is comparatively lesser than what we expected. Same thing goes for the probability of low risk. The values for high or low risk may be oscillating between 16.67% and 25%, if we were to create a dynamic model for the automotive industry.
- Overall, the net effect of high risk probability (16%) is smaller than expected (27%) on the target child node.
- Thus we can easily conclude from the above posterior probabilities that the automotive industry in India is well cushioned for high risk environments.

Now we will conduct sensitivity analysis for the Bayesian network model. We conduct sensitivity analysis using tornado graph to see the effect of risk factors on the gross turnover of the Indian automotive industry. If the Bayesian Network has a target variable, a sensitivity analysis (Jensen & Neilson, 2007) is also useful to determine which variables and states of the variables are most influential with respect to the target variables. In a tornado graph, the factor having the greatest effect on the target node is located on the top, and the extremes of the bar, that is the ends of it, indicate the low and high value of the risk factor (Sharma and Saurabh, 2015). This will tell which are the most critical risk factors, sort and prioritize them according to their impact on the gross turnover of the industry and decide where additional efforts by the industry are needed to improve risk mitigation.

When we hover over the tornado chart bars in GeNIe, it shows the following parameters:

- **Target value range**: The min/max posterior values for the node/outcome selected in the dropdown list above the tornado. The minimum and maximum depend on the changes allowed in parameters by the selection you make using the 'Parameter spread' slider below the tornado.

- **Parameter range**: Min/ max parameter value. Again, this is controlled by parameter spread.
- **Current parameter value**: The probability in the conditional probability table (CPT) of the node at specified index. The index is a linear representation of the parent configuration displayed above the tornado bar (after the | sign).
- **Derivative**: The value of the first derivative for the function which outputs the target posterior, given the parameter represented by tornado bar. This function (not the derivative) has the general form T= (a * p + b) / (c * p + d), where T is target posterior and p is the parameter under study. Sensitivity code calculates these coefficients. When they're known it's trivial to obtain the derivative, which is the basic measure of sensitivity, and target posterior range (see 1 above)
- **Coefficients**: a, b, c, d values for the function described above.

We set the Target node value 'High', 'Medium' and 'Low' and check the relative importance of parent nodes affecting the target node. The following Figs. 4.7, 4.8 and 4.9 will tell us the sensitivities of the three main factors on the gross turnover of the industry.

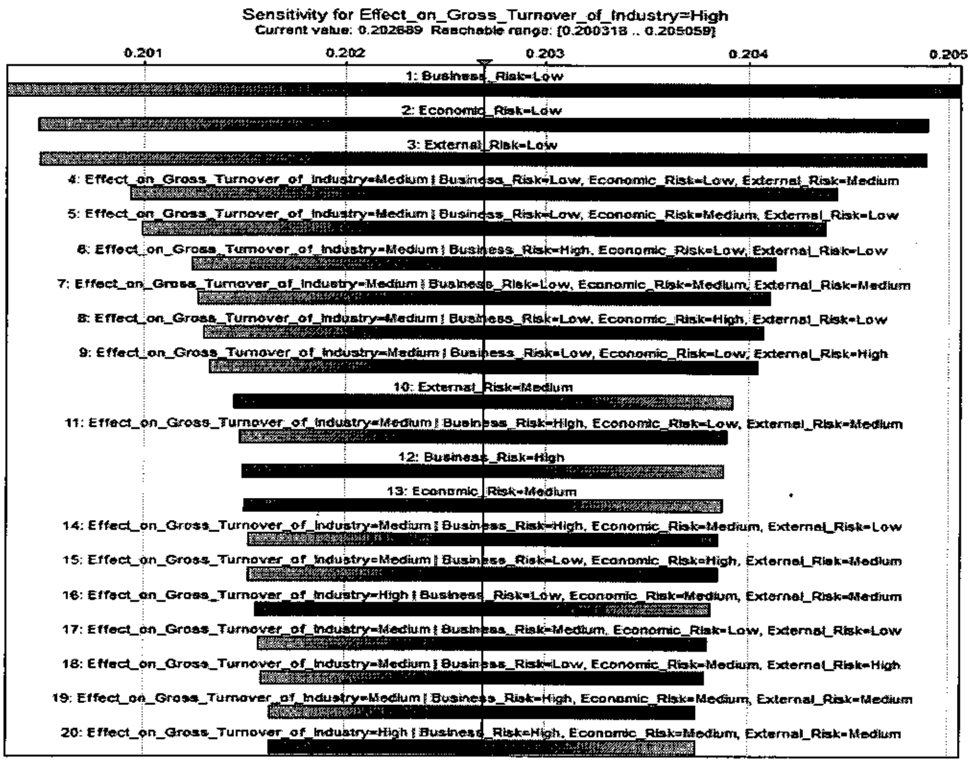

Fig. 4.7: Sensitivity Analysis Report when Target Node is set to 'High'

Source: Singh et al. (2018)

The above figure shows that the same CPT which we saw earlier into a pictorial diagram.

- The high risk probability for the net turnover is considerably low (22.22%) when economic and external risk probabilities are at medium risk but the business risk probability is low risk.
- When two of them are at medium risk probability and one of them is high risk, then the target node has an overall risk probability of only 25%, which is quite low considering the parent nodes are at medium and high risks.
- Whenever two of the three risk factors are at low risk and one of them is at medium risk, the high risk probability of net turnover has been observed to be at 16.67%.
- Probability of high risk effect on the gross turnover of the industry has been observed to be low compared to medium and low risk, ranging from 16.67% to 25%. This shows that the industry is not overly exposed to high risk due to any of the three risk indicators.

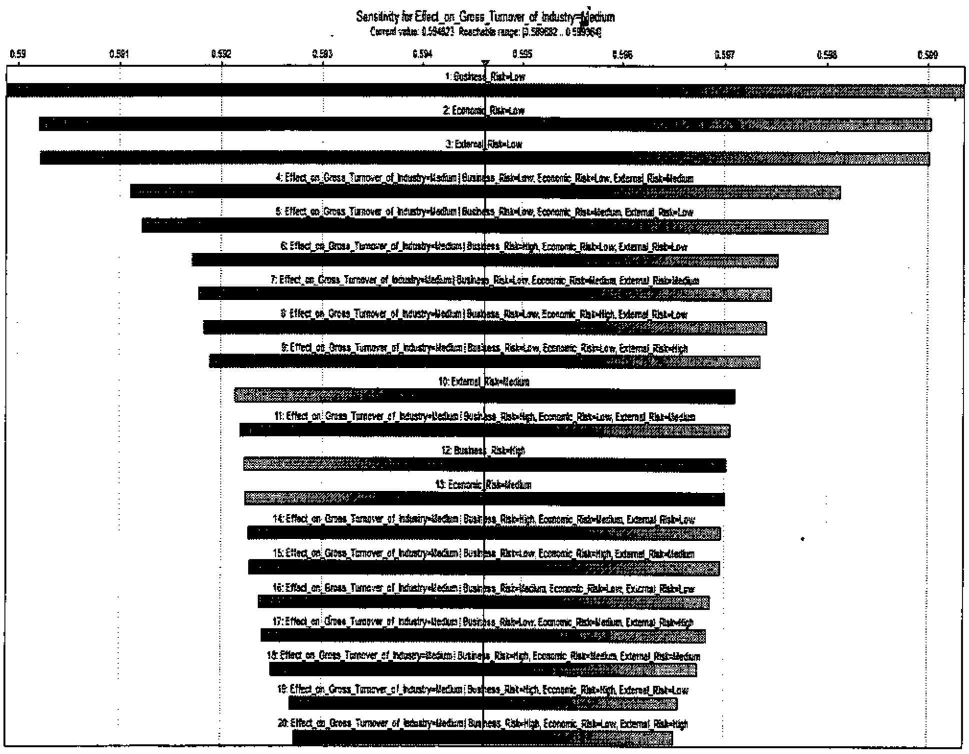

Fig. 4.8: Sensitivity Analysis Report when Target Node is set to 'Medium'

Source: Singh et al. (2018)

When two of them are at medium risk probability and one of them is low, then the target node has an overall risk probability of 55.56% which is lower than 66.67%. The reason for this can be that two medium risk nodes are positively correlated with each other and that it might lower the risk probability on the net turnover of the industry.

- The medium risk probability for the net turnover of the industry is generally between 50% and 66.67% when the one of the three factors is low and the other two are at medium risk probability.
- The medium risk chance on the net turnover of the industry is at 50% when we have all the factors - business, economic and external risk at medium risk probability.
- There is a 55% which is medium risk possibility for the net turnover of the industry when business risk probability is low and the economic and the external risk probabilities are high. This shows that the economic and external risk factors are positively correlated to some degree.
- The medium risk probability for the net turnover is considerably high (66.67%) when economic and business risk probabilities are low but the external risk probability is medium. The same is true when economic risk probability is medium and business and external risk probabilities are low.

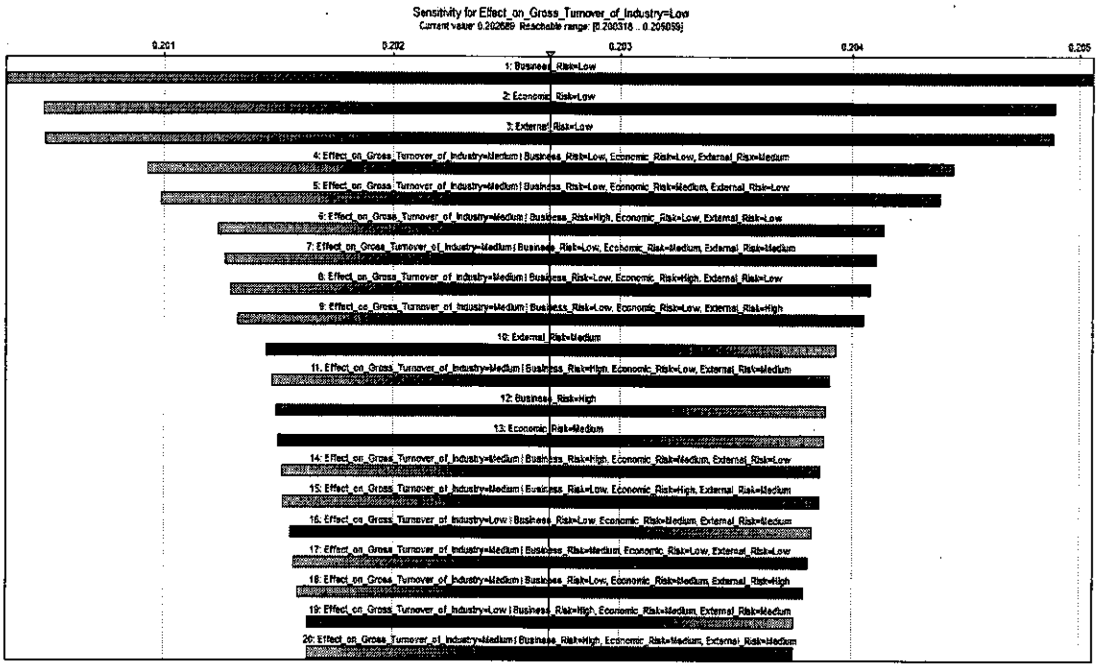

Fig. 4.9: Sensitivity Analysis Report when Target Node is set to 'Low'

Source: Singh et al. (2018)

- The probability of low risk effect on the net turnover of the industry due to low business risk, medium economic risk and medium external risk is at 22%, which is very low. This can be explained as the economic risks and external risks are positively correlated.
- The low risk probability of the net turnover of the industry, when the business risk is high, economic and external risk are low, is low, as expected at 16.67%.
- The industry cannot be at low risk. This can be seen from the bar where the business risk is high, and the economic and external factors are at medium risk. The probability of low risk on the net turnover of the industry for this bar is at 25%. Hence, the industry is mainly exposed to medium risk.

4.6 Conclusions

From the analysis above, it can be concluded that the automotive industry in India is well cushioned for high risk environment. As the above posterior probabilities show, the probability of high risk of the gross turnover of industry is 16%, which is very low compared to the amount of risk factors in play. Same goes for the low risk of the gross turnover of the industry. The probability of low risk effect is 21%, which is slightly higher. This shows that the industry has taken quite a few steps to rectify the amount of effect the risk indicators can have on its net turnover. The automotive industry in India is on the right path with its risk management. The risk factors are present in the industry, as their probabilities show that, though the industry has put in place certain counter measures.

Basic macro-economic factors have largely been taken from the financial statements of the companies, various articles, and news clippings. The auto mobile sector has a strong positive correlation with macro-economic factors. When framing the strategies for volatile and foreign environments, managers usually rely on country risk analysis to make their decisions. This is one of the major reasons for the inclusion of the country risk factor into our analysis.

Exchange rate risk is one of the major obstacles faced by both the domestic and the international companies in optimizing their supply chain networks. Companies are more exposed to exchange rate risk due to their large exporting and importing activities. Investigations into these exchange rate risks show that most of the companies are fairly well protected from it. Still to construct a generalized model for an industry, we included the factor into our analysis to observe the exposure of the Indian automotive sector to the exchange rate risk.

Supply network disruptions have been widely researched for all the industry sectors. Tier 2 stoppages, disasters, supplier financial stress, suppliers' union issues are some of the external factors that may lead to supply chain disruptions. The occurrence of any of the above events in the major countries from which a firm purchases materials for manufacturing its products or in which its finished goods are sold, may result in disruptions and delays in the operating activities of the company (Craighead et al., 2007). All these factors are taken from literature on risk management in automotive sector, and a generalized Bayesian network model has been constructed.

The effects of the sub-factors of the three main risk indicators – business risk, economic risk and external risk are not entirely projected in the final posterior probabilities. This may be due to some of the sub-factors may be correlated with each other. This results in one sub-factor cancelling out the effects of another sub-factor on the main factor (one of the parent nodes). This research may also be affected to some degree by sample selection bias, time-period bias and look ahead bias. For business risk, it is observed that high risk effect of the demand volatility sub-factor has been effectively dominated by the very low credit risk possibilities and the low R&D expenditure risk. For the economic risks, its sub factors - India's high growth potential (GDP and GNI per capita) and the booming index of industrial production have effectively brought down the high risk effects of exchange rate risk and country risk (look at it from an import-export view). As you can see from the model, the high risk is only 29% probable, with medium and low risk dominating at around 36% each. For external risks, the low raw material risk has brought down the high risk probability of the supply chain risk disruption. The high risk possibility is only 28%, which shows that the high risk factor, supply chain disruption effect has been cancelled out to a certain degree such that the probability of low and medium risk for the external factors has increased to 36% each. This is one of the drawbacks of constructing a very general, empirical model of a huge industry, where there are many complex factors in play.

Thus, proposed BN modelling captures both subjective and objective data and it is more useful in the situations where there is data scarcity (developing nations). To create a complex, accurate Bayesian network model for the automotive industry in India, more data and conditional probabilities with the help of companies' managers is needed. The specific contribution of this research is to provide a methodology and model for supply risk assessment. A detailed guideline for the data collection has been provided. In practice, companies lack the data in their databases but these days, data can be obtained from propriety firms or through many secondary sources. For the subjective factors like supply chain disruptions, a guideline has been provided to elicit the probabilities form experts. One of the important academic contribution of this research is to develop a supply risk model wherein for objective factors, secondary data has been collected.