Journal of Cleaner Production 108 (2015) 583–594

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Exploring role of environmental proactivity in financial performance of manufacturing enterprises: a structural modelling approach

Parag Sen [a,*], Mousumi Roy [b], Parimal Pal [a]

[a] Department of Chemical Engineering, National Institute of Technology Durgapur, 713209, India
[b] Department of Management Studies, National Institute of Technology Durgapur, 713209, India

ARTICLE INFO

Article history:
Received 12 April 2014
Received in revised form
19 May 2015
Accepted 19 May 2015
Available online 28 May 2015

Keywords:
Environmental proactivity
Financial performance
Structural modelling
Manufacturing enterprises
Operational performance

ABSTRACT

In the backdrop of overwhelming concern for greenhouse gas emission, global warming and overall environmental degradation, many manufacturing enterprises are now integrating their manufacturing philosophy with proactive environmental management approach. It is uppermost in the minds of many whether such environmental proactive approach will also help to improve financial performance of the manufacturing enterprises. This study explores this pertinent issue in the context of manufacturing enterprises of two democratic countries from the east and the west, India and UK respectively. Data collected through a questionnaire validated by invited experts distributed among manufacturing enterprises of India and UK were used to construct the structural model for testing the relationship between environmental proactivity and financial performance. The fitness and robustness of the structural model can be considered adequate. The results indicate positive correlation of environmental proactivity with financial performance, manufacturing based operational performance and non-manufacturing based operational performance. Model equations derived from structural analysis, however, reveal much stronger positive correlation of financial performance with manufacturing based operational practices than with the non-manufacturing based operational practices. The novelty of this research work lies in its managerial implications. It is suggested from the research that the manufacturing enterprises of India and UK should focus more on the manufacturing based operational practices than non-manufacturing based operational practices in order to improve environmental and as well as financial performance.

1. Introduction

Businesses across the world are undertaking phenomenal change in their production strategies by incorporating the concept of sustainable development. This has become imperative due to deteriorating environmental health owing to emissions of greenhouse gases (GHG) and other polluting substances from manufacturing. Lifecycle analysis of many such products indicates their disastrous footprint on the mother earth. This has necessitated environmental proactive role in running business. Manufacturing enterprises small, medium or large contribute significantly to GHG emission. Environmental quality is further degraded by discharge of solid wastes and wastewater from their operations (Kumar and Pal, 2013a, 2013b; Swain, 2006; Pizer et al., 2011; Marshall et al., 2013). Energy inefficiency and inefficient supply chain also lead to increased emission and generation of more wastes affecting the environment as well as financial performance of the manufacturing enterprises. There are a number of good reasons to get involved in taking action on climate change from the industrial perspective. Such actions may reduce cost and increase revenue, reduce the risks associated with higher energy costs, develop appropriate strategies for reduction of greenhouse gas emissions, and initiate proactive approaches for both preventive and corrective measures, along with compliance with government-initiated regulations. The manufacturing enterprises all over the world are thus bound to adopt environmental proactive approach (Swain, 2006). But the question of whether such an environmental management approaches will lead to better financial performance or not is arising in the minds of the entrepreneurs. This issue needs to be particularly examined in the contexts of manufacturing sectors of both the developing and the developed countries where India and UK are two fit cases for this study.

* Corresponding author. Tel.: +91 9830562645.
E-mail address: paragbelurmath@gmail.com (P. Sen).

http://dx.doi.org/10.1016/j.jclepro.2015.05.076
0959-6526/© 2015 Published by Elsevier Ltd.

India is a developing economy of the east and UK is a developed economy of the west. Manufacturing is a top priority in both India and UK. India has recently launched a national manufacturing policy that aims to increase manufacturing activity from a current 16% of Gross Domestic Product (GDP) to 25% by 2022 in order to achieve a growth rate of 12–14% per year. Government of UK also announced a series of policy on advanced manufacturing. Apart from manufacturing similarity in terms of technology and operations, both the countries face similar kind of challenges to develop their manufacturing strategies (UK and India Partnership in Advanced Manufacturing Research Challenges, 2012; Shapira et al., 2014). In environmental quality excellence awards, UK ranks just after India (IBEF, 2013). In both the countries, stakeholder's pressure as to cleaner production is a key issue for consideration. The issues of green product design, green manufacturing and green supply chain management including boundary-spanning activities such as green purchasing and practice of reverse logistics are gaining importance in these two countries (Binder and Neumayer, 2005; Kapila et al., 2011; Baud and Dhanalakshmi, 2007).

Thus in this paper, manufacturing enterprises of India and UK have been considered collectively for evaluation purpose with the aim of testing the relationship between environmental proactivity and financial performance of manufacturing enterprises. The relationships of environmental proactivity with non-manufacturing based operational performance are also evaluated (as pre-requisites of the main objective). Structural equation modelling (SEM) is used in the study as it applies effective statistical tools for testing and estimating causal relations between latent or unobserved variables allowing both confirmatory (theory testing) and exploratory modelling (theory development). Identification of the constructs and variables from literature with respect to the objective as per hypotheses is essential to successful structural equation modeling (Jabbour et al., 2013; Sambasivan et al., 2013). Information about rest of the paper is organized as follows. Literature review is discussed in section 2. Research methods and data collection are discussed in section 3. Research hypotheses are provided in section 4. Results and discussion are illustrated in section 5 and the conclusions are provided in section 5.

2. Literature review

Eco-friendly manufacturing is considered as an economically driven integrated approach that seeks reduction and elimination of all waste streams associated with the design, manufacture, use and disposal of all involved materials, and products (Curkovic, 2003). Life cycle assessment is also considered a sustainable tool for environmentally friendly manufacturing that takes into account product design, manufacturing and life cycle activities. Benefits of clean production do not remain confined to reduction of adverse environmental impacts only (Choi et al., 1997) but also lead to better product acceptability. Environmentally conscious customers demand product functional design complying with environmental regulations (Smith and Yen, 2010). Hence development of green processes and products can be a way for manufacturing enterprises to achieve competitive advantage with financial benefits (Porter and Linde, 1995; Dangelico and Pontrandolfo, 2010). Proper environmental management system (EMS) should have an integrated and holistic approach to improve environmental and financial performance (Hui et al., 2001).

Decisions about green initiatives are taken by the top management of the manufacturing enterprises to improve environmental performance by applying the principles of sustainability (Vachon and Klassen, 2008; Kneller and Manderson, 2012; Toke et al., 2012). Environmental proactivity often gets reflected in the approaches of manufacturers to get ISO 14001 certificates (Jabbour et al., 2013; Sambasivan et al., 2013; Arimura et al., 2011). Many manufacturing enterprises are now considering 'reduce-recycling-reuse' (3R) concept to reduce raw material and water consumption. Reducing raw material and water consumption not only helps to prevent rapid depletion of natural resources, but also helps the manufacturing enterprises to save financially (Jayal et al., 2010; Sarkis, 1995).

However, it is not clear whether the environmental proactivity is positively related to the financial performance of the manufacturing enterprises of India and UK. Particularly, in case of limited financial resources how environmental proactivity influences financial performance, it is found controversial among the researchers (Sambasivan et al., 2013; Iwata and Okada, 2011). Governments of both these countries like many other governments of the developed as well as developing economies have applied increased focus on improving the attractiveness of the location for manufacturing enterprises through the formation of local clusters (IRMA, 2009). Formation of local clusters promotes regional development by providing various opportunities for improving environmental and economic performances of the enterprises (Planning Commission, Government of India, 2013). Researchers like Sambasivan et al. (2013) and Jabbour et al. (2013) have proposed a number of constructs (latent variables) and variables (manifest variables) that can influence the financial performance of the manufacturing enterprises through environmental proactivity. The importance of the variables can vary from country to country depending on the size of the countries. However, in this paper, all major possible variables for the proposed factors have been considered though literature shows that there may be overlapping of the variables. Such overlapping has been avoided in this work by selecting only the proper and exact variables. Five-point scale has been used to measure the degree of the variables as it is easier to mark for the decision makers compared to other point scales (Sambasivan et al., 2013; Jabbour et al., 2013).

Environmental proactivity (EP) deals with 11 variables as found from different literature. EP plays an important role at strategic level environmental decision making. EP involves (i) top management support or manpower involvement, (ii) approach to increase environmental expenditure, (iii) maintain regulations imposed by the governments and stakeholders, (iv) formal environmental management system, (v) total quality management system, (vi) long term sustainable initiatives, (vii) recycling initiatives, (viii) intelligent environmental management, (ix) life cycle assessment, (x) eco-design, and (xi) environmental risk management system. Environmental proactivity can help an enterprise to improve its operational performances based on manufacturing and non-manufacturing activities. Environmental proactivity can also lead to improve the financial performance through operational performances (Sambasivan et al., 2013; Toke et al., 2012; Jabbour et al., 2013).

Manufacturing based operational performance (MOP) involves six variables namely (i) reduction of emission to air, (ii) greener overall manufacturing system, (iii) reduction of energy consumption, (iv) reduction of raw material consumption, (v) reduction of water consumption, and (vi) reduction of wastes. Normally, manufacturing process itself is considered the significant source of environmental pollution because of formation of chips, smoke, dust and application of coolants, different chemicals or hazardous materials. From the variables, it is clear that MOP considers the prevention or controlling activities against environmental pollution or affects occurred during the time of manufacturing or because of manufacturing process (Toke et al., 2012; Setiawati et al., 2013; Sambasivan et al., 2013).

Non-manufacturing based operational performance (NOP) also deals with six variables. NOP involves (i) sale of scraps/wastes/excess materials, (ii) rating of customer satisfaction, (iii) environmental auditing of suppliers, (iv) adoption of green transportation, (v) green packaging, and (vi) societal concerns. From the variables, it is clear that NOP considers the prevention or controlling activities against environmental pollution occurred other than the manufacturing process (outside of production-line). NOP leads to improve the overall quality of the enterprises while gaining financially (Toke et al., 2012; Sambasivan et al., 2013; Silva et al., 2013).

Financial performance is the most important criteria from the perspective of any enterprise as the ultimate goal of any manufacturing enterprise is making money. Financial performance is assessed by (i) increased revenue, (ii) increased profit/reduction of production cost, and (iii) increased return on equity and cash-flow. Turnover is the income of an enterprise from its product sale and revenue gross sale or turnover including asset sale. While return on equity is given by the ratio of net income and shareholder's equity, cash-flow considers any movement of money into or out of a business or product over a specific period of time. Cash-flow can be used to evaluate the quality of income generated by accrual accounting which is the addition of interests or different investments over a period of time (Setiawati et al., 2013; Endrikat et al., in press; Toke et al., 2012). All the constructs and variables are provided with their sources in Appendix 1.

Majority of researches have revealed that environmental proactivity is positively related to the operational performance irrespective of its nature (i.e. manufacturing or non-manufacturing based) (González-Benito and González-Benito, 2005; Sambasivan et al., 2013). However, it is found quite controversial among the researchers whether the environmental proactivity really helps the enterprises to improve their financial performance. For example, while the earlier studies (Walley and Whitehead, 1994; Newton and Harte, 1997) conclude that there is no significant relationship between environmental proactivity and financial performance, recent studies (Claver et al., 2007; Sambasivan et al., 2013) argue that there is a positive relationship between the environmental proactivity and financial performance. Sueyoshi and Goto (2010) observe that the relationship between environmental proactivity and financial performance is largely affected by the size of the enterprises. For large enterprises environmental proactivity is positively related to financial performance. However, for small and medium enterprises (SME) environmental proactivity has no significant impact to improve the financial performance.

3. Research methods and data collection

Research methods are the systematic and theoretical analyses of the methods applied to a specific field of research for solving a particular problem to ascertain the best possible practices. Based on the existing gap in research involving environmental proactivity, manufacturing and non-manufacturing based operational performance and financial performance of the manufacturing enterprises of India and UK, it was decided to conduct a quantitative research (Fig. 1.). Manufacturing enterprises (large and SMEs) of India and UK were the target area of this research as the manufacturing sectors of India and UK contribute more than 10% to the gross domestic product (GDP) employing around 9% and 8% of the total working population respectively. As per 2010 statistics, India is the 10th largest manufacturing nation in the world followed by UK (Planning Commission, Government of India, 2013; BIS, 2010).

Manufacturing sectors of India and UK can be classified into four categories depending on the use of products, namely (i) Basic goods (e.g. finished steel, fertilizers, cement, steel casting, pipes and tubes, stamping and forging); (ii) Capital goods (e.g. commercial vehicles, auto components, electric motors, railway locomotives, textile machinery, machine tools, electric generators, ship building, tractors); (iii) Intermediate goods (e.g. cotton yarn, tyres, tin metal containers, bolts and nuts) and (iv) Consumer goods (e.g. sugar, tea, soaps, paper and paperboards, medicines) (IBEF, 2013; National Statistics, 2007).

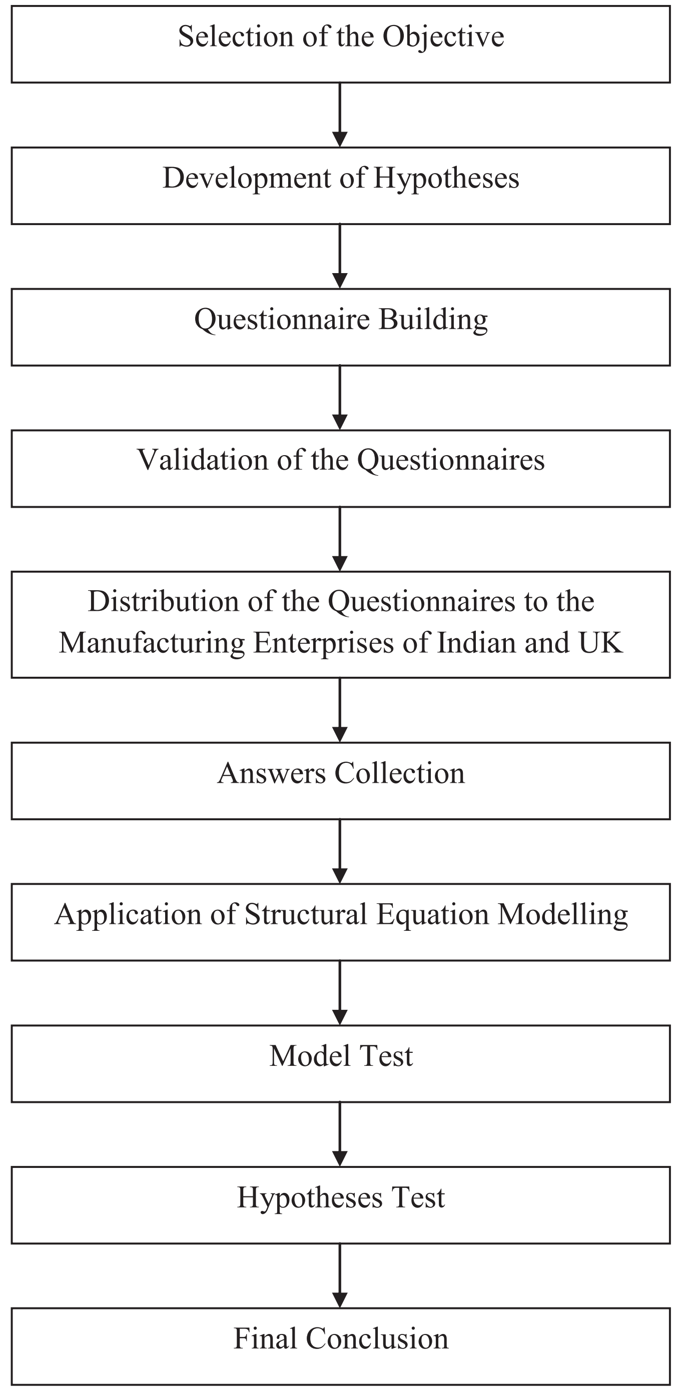

Fig. 1. Flow diagram for research methods of survey.

This study includes major manufacturing enterprises except those which do not involve machining or metal forming. After identifying the research gap, hypotheses were developed which are described in the next section. Then questionnaires were built with the aim of testing the hypotheses. Manufacturing enterprises of India and UK had been considered collectively for this research. The

Table 1
Details of responses of the delivered questionnaires.

Country	Small and medium scale enterprises (SME)							Large scale enterprises (LSE)						
	A	B	C	D	E	F	G	A	B	C	D	E	F	G
India	358	62	17.32%	2	3.23%	60	16.76%	151	67	44.37%	3	4.48%	64	42.38%
UK	301	65	21.59%	1	1.54%	64	21.26%	100	65	65.00%	2	3.08%	63	63.00%

A = Total number of delivered questionnaires B= Number of collected answers C= Percentage of response rate D = Number of discarded questionnaires E = Percentage of discarded questionnaires (of the collected answers) F= Number of accepted answers G = Percentage of accepted answers (of the sent questionnaires).

manufacturing enterprises included SMEs and large scale enterprises. In India, SMEs are defined as enterprises where investment in plant and machinery up to Rs. 10 crore or 100 million, but in UK SMEs are defined as enterprises where the number of employees are up to 250.

The questionnaires were validated by the invited experts (who occupied the highest position in production/operations/environmental areas) from different manufacturing enterprises of India and UK in a workshop meeting. All the experts were well experienced in the area of environment and manufacturing/operation. It was found that all the items (constructs and respective variables) collected from literature were valid as per the opinion of the experts and no extra item was added to the formed questionnaires as it contained all the necessary major variables.

The research data were collected during the period May 2013 to January 2014. The lists of the companies with addresses and email information were collected from the lists of industrial directory available on the websites.[1] The validated questionnaires were sent to different manufacturing enterprises of India and UK through postal mail and e-mail to collect the answers. Emails containing questionnaires and brief objective and explanation of this research, were sent to the respondents occupying the highest positions in production/operations/environmental areas in the manufacturing enterprises followed by phone calls to contact the employees of the enterprises in order to increase the number of answers. The questionnaires contained four sections, each for one construct. Under EP, MOP, NOP and FP construct, participants were requested to mark based on a 5-point scale where the degrees of 1, 2, 3, 4 and 5 were used to represent 'not at all', 'to little extent', 'to some extent', 'to a moderate extent' and 'to a large extent' respectively. There were a total of twenty six variables to be marked; under construct EP there were eleven variables, under construct MOP there were six variables, under construct NOP there were six variables and construct FP contained three variables.

The questionnaires were then sent to a total of 910 manufacturing enterprises out of which 358 enterprises from India were SMEs (ISME), 151 enterprises from India were large (ILSE), 301 enterprises from UK were SMEs (UKSME) and 100 enterprises from UK were large (UKLSE). A total of 259 answers (28.46% of the total questionnaires sent) were collected from different manufacturing enterprises of India and UK; among them 62 answers (response rate 17.32%) were from ISME, 67 answers (response rate 44.37%) were from ILSE, 65 answers (response rate 21.59%) were from UKSME and 65 answers (response rate 65%) were from UKLSE. This indicates that the response rate is lower in India (see Table 1). Out of these 259 answers, 8 answers (0.03% of the total answers) were discarded (2 answers from ISME, 3 answers from ILSE, 1 answer from UKSME and 2 answers from UKLSE) due to being incomplete, leading to a total response rate of 27.58% which was greater than 6%[2] for 251 valid responses (valid response rates for ISME, ILSE, UKSME and UKLSE are 16.76%, 42.38%, 21.26% and 63% respectively) and can be considered adequate at total and as well as individual level (i.e. ISME, ILSE, UKSME and UKLSE) for applying structural equation modelling (SEM) as suggested by a number of researchers (Large and Thomsen, 2011; Jabbour et al., 2013; Sambasivan et al., 2013).

SEM[1,3]considers general linear model to evaluate how well the hypothesized structure fits[2] the data using maximum likelihood[3]. Structural equation modelling is done following the steps below.

Step 1 The missing values of the collected data are first checked. For the missing values of data, Little's Missing Completely at Random (MCAR) Test[4] is performed to check whether the missing data are completely at random. Normally, if the p-value[5] is greater than 0.5, it indicates that the data missing is completely at random. Mean value replacement is considered as the recommended option for missing value treatment (Armstrong and Overton, 1977).

Step 2 The second step is to group variables into factors using Principal Component Analysis (PCA) with the objective of reducing a set of variables down to a smaller number of factors in order to create composite scores for these factors for use in subsequent analysis. PCA is done using varimax method[6] to extract factors having eigen values greater than 1, from the constructs to indicate how much data cloud variance is absorbed by it. The accumulated (total) variance for each construct is expressed with its eigen value. Anti-image correlation matrix contains the negatives of the partial correlation coefficients, and the anti-image covariance matrix contains the negatives of the partial covariance. Most of the off-diagonal elements are small to indicate a good factor model. Main diagonal values of the anti-image matrix are greater than 0.6, however slight less values also are accepted (Jabbour et al., 2013). The values of the loadings[7] and communalities[8] (to explain the adherence of a given variable to the diverse factors of a factorial analysis as mentioned by Jabbour et al., 2013) of all variables for a particular construct are expressed from component matrix and reproduced correlations to show which particular variable is loaded on which particular factor and which variables are not significant (having communalities less than 0.5).

Step 3 To assess the fitness of the model, Kaiser-Meyer-Olkin (KMO) Test, Bartlett's Test of Sphericity (BTS) in terms of Chi-square and p-value, reliability test (using Cronbach's alpha) are performed.

KMO Test is used to verify the correlation value between the variables. More the value of the KMO Test is near to one and zero, more the sample size is adequate and inadequate respectively. The

[1] http://indiaindustriesdirectory.com/http://www.ukdirectory.co.uk/manufacturing-and-industry/manufacturing/.

[2] Murillo-Luna et al. (2011) suggest that a response rate greater than 6% can be considered adequate to apply SEM.

[3] Important statistical terms are expressed with their cut-off values (if any) in Appendix 2 as suggested by Meyers et al., 2005; Sambasivan et al., 2013 and Kenny, 2014.

acceptable value is considered greater than 0.5; between 0.7 and 0.8 is good and 0.9 or above is excellent.

BTS considers the hypothesis that the correlation matrix is the identity matrix where the determining factor is equal to one in order to analyze the correlation matrix as a whole. Bartlett factor scores have a mean of 0 and the sum of squares of the unique factors over the range of items is minimized. Reliability analysis for each construct is performed in terms of Crobach's alpha to measure the internal consistency (i.e. how closely related a set of items are as a group), acceptable value of which is greater than 0.7 (Kline, 2005).

Step 4 The basic correlation matrix and the descriptive statistics (average and standard deviation of the variables) are presented.

Step 5 Before running the SEM model, the appropriate method for SEM is selected. Partial Least Squares (PLS), dealing with second generation multivariate analysis is used to deal with complex theories like environmental related issues or in empirical research works/initial stages of development. To generalize framework for multi-block analysis, PLS has the advantage of systematic convergence of the algorithm due to its simplicity, possibility of managing data with a small number of individuals and a large number of variables with practical meaning of the latent variable estimates. PLS-SEM is a two-step method; while the first step deals with computing the latent variable scores using the PLS algorithm, the second step deals with carrying out Ordinary Least Square (OLS)[9] regressions on the latent variable scores for estimating the structural equations. Once the PLS-SEM is run, it should be stopped within 300 iterations (general case) for the identified model. If the PLS-SEM algorithm does not converge within 300 iterations, the algorithm could not find a stable solution which almost never occurs.

Step 6 Now, Average Variance Extracted (AVE), Compounded or Composite or Construct Reliability (CR), Coefficient of Determination (R^2)[10] and communality are determined for each construct.

AVE measures the amount of variance captured by a construct in relation to the variance due to random measurement error (Sambasivan et al., 2013). The formula for variance extracted (VE) is given below using standard notations (as used by Meyers et al., 2005) λ to represent the standardized factor loadings and n to represent the number of items.

$$VE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n}$$

CR is a measure of overall reliability of a collection of heterogeneous but similar items (Sambasivan et al., 2013) and is expressed by the following equation using standard notations (as used by Meyers et al., 2005) λ to represent the standardized factor loadings, n to represent the number of items and δ to represent error variance.

$$CR = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \left(\sum_{i=1}^{n} \delta_i\right)^2}$$

R^2 values near 0.75, 0.5 and 0.25 are considered as substantial, moderate and weak respectively, indicating how much (%) of the variance can be explained by the variables used in the concerned regression equation (Hair et al., 2011).

To assess the construct validity (refers to the degree to which a measure assesses the theoretical construct it is supposed to assess) of the model, convergent validity and discriminant validity can be tested. Convergent validity is considered when the variables do not correlate well with each other within their parent factor (construct), indicating the construct (latent variable or unobserved variable) is not well explained by its variables (manifest or observed variables). To test convergent validity, the values of AVE are greater than or equal to 0.5 and the values of CR are greater than AVE (Foltz, 2008), or greater than or equal to 0.7 (Sambasivan et al., 2013). Discriminant validity is considered when the variables correlate more highly with variables outside their parent factor than with the variables within their parent factor, indicating the construct is better explained by some other variables (from a different construct), than by its own observed variables. To test discriminant validity, cross-loadings are examined. Discriminant validity is achieved when an indicator's loading on a construct is higher than all of its cross-loadings[11] with other constructs (Meyers et al., 2005).

Step 7 The complete SEM model is demonstrated by acceptable level of absolute fit[12] expressed in terms of Goodness-of-fit Index (GFI).

Normally, the overall statistical fitness of the model is expressed by Goodness of Fit (GoF) statistics which have values 0.10, 0.25 and 0.36 for GoF-small, GoF-medium and GoF-large respectively (Wetzels et al., 2009). Goodness-of-Fit Index (GFI) (should be greater than 0.90) is the proportion of variance in the sample correlation/covariance accounted for by the predicted model as (Meyers et al., 2005):

0: No fit$\leq$ GFI$\leq$ 1: Perfect fit.

Step 8 Finally, a bootstrap of 1000 sub-samples, drawn from the original sample with replacement (i.e. each time an observation is drawn at random from the sampling population, it is returned to the sampling population before the next observation is drawn) is used to test the robustness of the model in order to estimate the statistical significance of relationships between mentioned variables and constructs expressed in terms of outer loadings (Jabbour et al., 2013).

Sign indeterminacy of latent or construct variables results in arbitrary sign changes of the bootstrap coefficients, compared to the estimates obtained from the original sample. This occurrence of sign changes pull the mean value of bootstrap results (i.e. outer weight) towards zero increasing the corresponding bootstrap standard error and hence ultimately decreasing the t-value as t-value is given by the ratio of outer weight and standard error. Hence individual sign change is considered to obtain the highest t-values[13]. However, if the result (path) is not significant, construct level change is considered to compromise between no sign change and individual sign change (Wold, 1985).

t-test values near 1.65, 1.96 and 2.58 reflect significance levels of 10%, 5% and 1% respectively [i.e. $\alpha = 0.10$, 0.05 and 0.01 or 90%, 95% and 99% of Confidence Interval (CI) respectively] (Hair et al., 2011).

4. Research hypotheses

This section proposes the research hypotheses. Enterprises may be proactive towards environmentally friendly manufacturing programmes if they recognize that improved environmental performance creates value for the enterprises. EP offers a structured approach to decision making in facilitating an economic and environmentally friendly production. A proactive strategy focuses on eliminating the source of potential problems rather than highlighting the problems after they have occurred. Manufacturing enterprises are considered environmentally proactive when they respond to challenges by adopting different environmentally friendly strategies in order to minimize the environmental impact. Environmentally proactive manufacturing enterprises commit resources to environmental management on an as-needed basis. EP deals with strategic level different kinds of environmental decisions making by the top management including environmental expenditure, life cycle assessment, intelligent environmental management and risk management for long-term sustainable growth of the manufacturing enterprises. MOP deals with lean manufacturing practices and energy and carbon footprint reduction technologies. MOP indicates formal routines and procedures that are used by the managers and employees to maintain or improve the environmental performance of operational practices. MOP includes practices aimed at improving operational and environmental performances as per strategic plan. Thus, it is quite expected that EP positively correlates with manufacturing based operational performance and this has been addressed by different researchers from countrywise and sector-wise (Sambasivan et al., 2013; Jabbour et al., 2013; Toke et al., 2012; Wisner et al., 2010). In India and UK, all the activities, related to MOP and EP are largely performed by the manufacturing sector. However for the Indian and UK manufacturing sector it has not been brought forth by the researchers. Hence, the first hypothesis is stated as follows:

Hypothesis 1. (H1): Environmental proactivity (EP) has a positive correlation with manufacturing based operational performance (MOP).

NOP deals with green supplier selection and various types of non-manufacturing related environmental impact control methods including improvement in transportation systems and packaging. It is quite expected that the strategic level environmental decision making helps to improve the NOP which has been highlighted by several researchers focusing on different countries and sectors (Jaber and Saadany, 2009; Silva et al., 2013; Toke et al., 2012). However for the Indian and UK manufacturing sector the relationship between EP and NOP has not been addressed by the researchers though in both the countries the activities related to EP and NOP are greatly performed. Hence, the second hypothesis is stated as follows:

Hypothesis 2. (H2): Environmental proactivity (EP) has a positive correlation with non-manufacturing based operational performance (NOP).

The relationship between EP and FP, it is quite controversial among the researchers, particularly in case of obsolete and

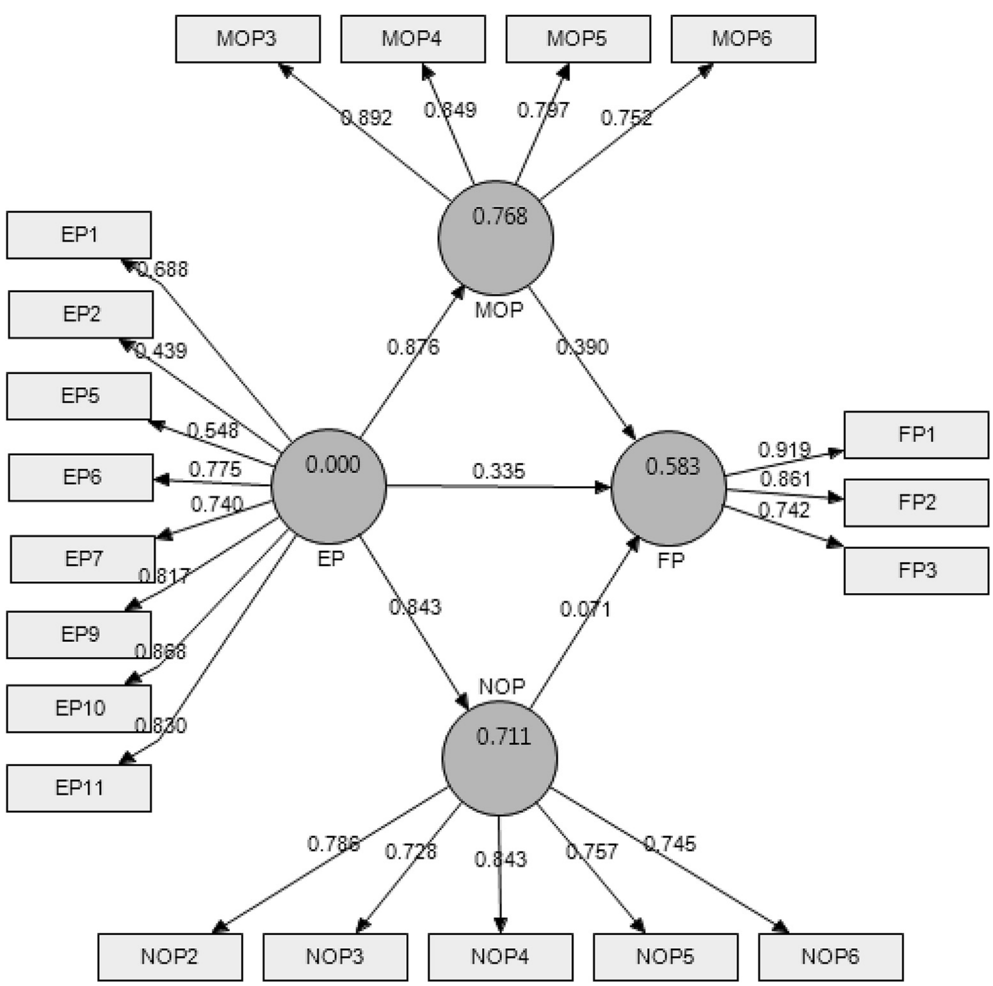

Fig. 2. Structural model for original data set.

inefficient technologies due to lack of financial resources (Sambasivan et al., 2013; Iwata and Okada, 2011; Planning Commission, Government of India, 2013). The manufacturing enterprises, in both the countries, are to take initiatives to control the environmental impacts and maintain the regulations imposed by the governments. Hence environmental expenditure is a key issue for every manufacturing enterprise. After investing money to control the environmental impacts, every manufacturing enterprise wants to get environmental and financial benefits from its initial investment, because manufacturing enterprises are required to recoup the funds expended in environmental investment. It is thus essential to find out the relationship between EP and FP for the large scale enterprises and SMEs, in India and UK. Hence, the third hypothesis is stated as follows:

Hypothesis 3. (H3): Environmental proactivity (EP) has a positive correlation with financial performance (FP). It can be expressed in terms of MOP and NOP if the previous mentioned hypotheses (i.e. H1 and H2) are proved.

5. Results and discussion

After collecting the complete answers, the data are analyzed using SPSS 16 and Smart-PLS 2.0. In the research, for the just-identified model (i.e. Degrees of Freedom is greater than zero), only complete answers were considered with no missing data. Hence, Little's Missing Completely at Random (MCAR) Test is not required to check whether the missing data are completely at random. There is no such column (variable) where all the items are identical and the data for the variables are non-normally distributed.

Variables of construct EP, MOP, NOP and FP are grouped into factors using Principal Component Analysis (PCA) through the varimax method, explaining an accumulated variance of 56.35%, 54.365%, 54.164% and 71.344% with eigen values of 5.259, 2.575, 2.908 and 2.14, and acceptable values of the main diagonal of the anti-image matrix (0.831, 0.727, 0.736, 0.866, 0.914, 0.906, 0.884 and 0.877), (0.796, 0.833, 0.864 and 0.851), (0.872, 0.888, 0.840, 0.869 and 0.863) and (0.596, 0.638 and 0.744) respectively. To refine variables EP3, EP4, EP8; MOP1, MOP2 and NOP1 are excluded from the constructs EP, MOP and NOP respectively due to low communalities (0.406, 0.108, 0.423, 0.239, 0.448 and 0.342 respectively). No variables are extracted from construct FP as all the variables have communalities greater than 0.5. The values of the load and communalities are presented in Appendix 3A, 3B, 3C and 3D.

To assess the fitness of the model for constructs EP, MOP, NOP and FP, KMO test (values 0.863, 0.844, 0.864 and 0.643 respectively), BTS test [Chi-square 1215, 540.665, 487.393 and 266.109 (p-value<0.1 for all) respectively], and Cronbach's alpha (0.870, 0.842, 0.828 and 0.797) are performed, presenting all satisfactory values.

Pearson's correlation matrices for all the constructs are presented in Appendix 3E, 3F, 3G and 3H, and the descriptive statistics (average and standard deviation of the variables) for all the constructs are presented in Appendix 3I, J, K and L.

EP5, MOP6, NOP6 and FP2 have highest average among all the variables for constructs EP, MOP, NOP and FP respectively. Pearson's correlation matrices reveal that EP11-EP9, MOP4-MOP3, NOP4–NOP2 and FP2-FP1 variables have highest correlations among all other correlations for constructs EP, MOP, NOP and FP respectively.

The SEM algorithm stops to converge within four iterations. All the path coefficients (loads) are determined (see Fig. 2.). The discriminant validity is checked by examining the cross loadings, showing adequate results presented in Table 2. EP is positively related to MOP (path coefficient is 0.876), NOP (path coefficient is 0.843) and FP (path coefficient is 0.335). Thus all the three hypotheses are considered as true. Among the three constructs mentioned later, MOP is mostly or predominantly influenced by EP. From the structural model FP is expressed in terms of MOP and NOP like FP = 0.390 MOP + 0.071 NOP.

Now, AVE, CR, R^2, Cronbach's alpha and communalities are determined for constructs EP, MOP, NOP and FP respectively, presenting all satisfactory values (see Table 3).

The overall SEM model was demonstrated by an acceptable level of absolute fit measure of GoF-large (0.675) with an average R^2 of 0.687. Though GoF was a LISREL measure, however the value of GoF was calculated according to the equation used by Wetzels et al., 2009.

Finally, to test the model robustness, a bootstrap of 1000 subsamples was run to estimate the statistical significance of relationships between proposed variables and constructs with corresponding t-values (see Fig. 3 and Table 4) to demonstrate the significance level of the paths. Here also, all the three relationships were positively correlated; however FP was influenced by EP at a significance level of closely but less than 10%. MOP and NOP both were influenced by EP at a significance level of less than 1%. Hence, the bootstrapping model indicates that the structural model was considered as a robust model. From the bootstrapping model FP was expressed in terms of MOP and NOP like FP = 2.086 MOP + 0.400 NOP.

Table 2
Cross-loadings for evaluating discriminant validity. Bold values indicate that the specific cell values are greater than the other cell values for the same row.

	EP	MOP	NOP	FP
EP1	**0.688**	0.469	0.645	0.353
EP2	**0.439**	0.229	0.255	0.169
EP5	**0.548**	0.370	0.434	0.392
EP6	**0.775**	0.678	0.655	0.577
EP7	**0.740**	0.667	0.596	0.546
EP9	**0.817**	0.753	0.665	0.583
EP10	**0.868**	0.853	0.739	0.757
EP11	**0.830**	0.777	0.742	0.655
MOP3	0.828	**0.892**	0.808	0.646
MOP4	0.722	**0.849**	0.633	0.666
MOP5	0.660	**0.797**	0.580	0.593
MOP6	0.668	**0.752**	0.616	0.530
NOP2	0.616	0.589	**0.786**	0.532
NOP3	0.624	0.548	**0.728**	0.506
NOP4	0.747	0.704	**0.843**	0.588
NOP5	0.620	0.593	**0.757**	0.464
NOP6	0.639	0.668	**0.745**	0.478
FP1	0.728	0.720	0.630	**0.919**
FP2	0.629	0.649	0.569	**0.861**
FP3	0.477	0.476	0.478	**0.742**

Table 3
Reliability and validity values for the structural model.

Constructs	Average Variance extracted (AVE)	Composite reliability	R^2	Cronbach's alpha	Communalities
EP	0.528	0.896	0	0.868	0.478
MOP	0.680	0.894	0.768	0.841	0.644
NOP	0.597	0.881	0.711	0.831	0.582
FP	0.712	0.881	0.583	0.797	0.713

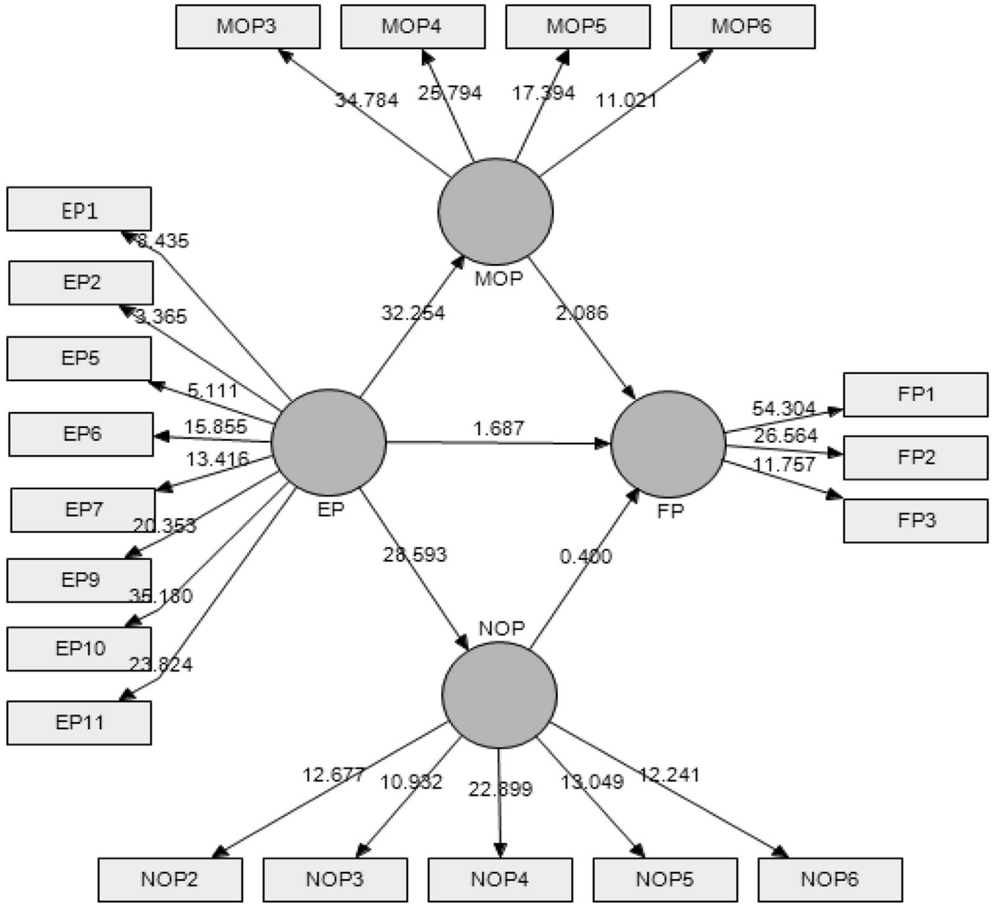

Fig. 3. Relationship between EP and FP with bootstrapping of 1000 sub-samples.

Table 4
Significance of model relationship coefficients.

Relationship	Load	T test	Significance level
EP1 ← EP	0.688	8.435	Less than 1%
EP2 ← EP	0.439	3.365	Less than 1%
EP5 ← EP	0.548	5.111	Less than 1%
EP6 ← EP	0.775	15.855	Less than 1%
EP7 ← EP	0.740	13.416	Less than 1%
EP9 ← EP	0.817	20.453	Less than 1%
EP10 ← EP	0.868	35.180	Less than 1%
EP11 ← EP	0.830	23.824	Less than 1%
MOP3 ← MOP	0.892	34.784	Less than 1%
MOP4 ← MOP	0.849	25.794	Less than 1%
MOP5 ← MOP	0.797	17.394	Less than 1%
MOP6 ← MOP	0.752	11.021	Less than 1%
NOP2 ← NOP	0.786	12.677	Less than 1%
NOP3 ← NOP	0.728	10.932	Less than 1%
NOP4 ← NOP	0.843	22.899	Less than 1%
NOP5 ← NOP	0.757	13.049	Less than 1%
NOP6 ← NOP	0.745	12.241	Less than 1%
FP1 ← FP	0.919	54.304	Less than 1%
FP2 ← FP	0.861	26.564	Less than 1%
FP3 ← FP	0.742	11.757	Less than 1%
EP → MOP	0.876	32.254	Less than 1%
EP → NOP	0.843	28.593	Less than 1%
EP → FP	0.335	1.687	Close but less to 10%
MOP → FP	0.390	2.086	Close to 5%
NOP → FP	0.071	0.400	Greater than 10%

6. Conclusions

It transpires that environmental proactivity and environmental performance are positively correlated. Financial performance (FP) is improved through manufacturing based operational performance (MOP) and non-manufacturing based operational performance (NOP). From the structural model, it can be seen that FP is predominantly influenced by MOP rather than NOP. Thus, it is quite expected that the enterprises which have strong manufacturing based operational practices to control environmental impacts are financially more benefited compared to the enterprises which focus non-manufacturing based operational practices.

Some important correlations are also found from this research as seen in Pearson's correlation matrices. Life cycle assessment (EP9) and environmental risk management system (EP11) are highly correlated. Similarly, increased revenue/turnover (FP1) helps to increase profit (FP2). Other correlations are not significant as such, confirming that the indicators chosen for the research do not overlap or repeat. It is suggested from the research that the manufacturing enterprises of India and UK should focus more on the manufacturing based operational practices to improve environmental and as well as financial performance. It is also suggested to assess the life cycle of products in order to improve the environmental risk management system.

Hence, these propositions have direct managerial implications, because the areas of manufacturing and non-manufacturing based operational performances are largely controllable by the production/manufacturing and environmental managers. Overall, this research gives a comprehensive view of environmental proactivity, manufacturing and non-manufacturing based operational performances and financial performances (from environmental perspective, i.e. due to environmental proactivity) of the manufacturing enterprises of India and UK.

However, this research also has its own limitations. In this research work, the manufacturing enterprises of India and UK are collectively considered. The comparison between the enterprises of the two countries is not addressed. Similarly, SMEs and large scale enterprises are collectively considered without doing the separation. Indian SMEs are not compared with the SMEs of UK. Indian large scale enterprises are not compared with the large scale enterprises of UK. These limitations flourish the scope of future research work which may be done based on the available data collected during the period of this research work as the sample sizes are relatively low but over 50 and in all the cases response rate is greater than 6%. Finally it is believed that future research work may disclose more relevant points.

Appendix 1. Variables related to different constructs and their sources

Constructs	Related Variables	Sources
Environmental Proactivity (EP)	EP1: Top management support/commitment and manpower involvement including environmental training	Toke et al., 2012; Sambasivan et al., 2013; Jabbour et al., 2013
	EP2: Approach to increase environmental expenditure (operational cost, training cost, environmentally friendly materials cost, waste and water treatment/recycling cost)	Sambasivan et al., 2013; Sueyoshi and Goto, 2009; Wang et al., 2014
	EP3: Approach to maintain regulations imposed by the government and stakeholders	Cong and Freedman, 2011; Zhu et al., 2013; Lannelongue and González-Benito, 2012
	EP4: Approach to have ISO 14001 certification or environmental policy or formal environmental management system (EMS) for green manufacturing (GM) and green supply chain management (GSCM)	Jabbour et al., 2013; Toke et al., 2012; Casadesús et al., 2008; Testa et al., 2014
	EP5: Approach to have total quality management system/ISO 9001 certification	Casadesús et al., 2008; Zhu et al., 2013; Terziovski et al., 2003
	EP6: Long term sustainable initiative regarding GM and GSCM over budget schedule	Toke et al., 2012; Sambasivan et al., 2013; Joung et al., 2012
	EP7: Recycling initiatives like joining local recycling enterprises or establishing collaboration with same sector/industry	Ricoh Group Sustainability Report , 2007, Toke et al., 2012; Tonjes and Mallikarjun, 2013
	EP8: Intelligent environmental management or communication management to exchange green initiatives among similar sectors	Mandal and Sarkar, 2012; Burke and Gaughran, 2006; Butler, 2011
	EP9: Life cycle assessment with environmental database of products	Zhu and Deshmukh, 2003; Hon and Xu, 2007; Chung and Wee, 2011
	EP10: Approach of green or eco-design (with cross-functional integration, if required)	Jabbour et al., 2013; Toke et al., 2012; Knight and Jenkins, 2009
	EP11: Environmental risk management system to decrease frequency of environmental accidents	Sambasivan et al., 2013; Ma et al., 2013; Zhao et al., 2010
Manufacturing based Operational Performance (MOP)	MOP1: Reduction of emission to air	Sambasivan et al., 2013; Pan et al., 2013; Changhong et al., 2006; Kuramochi et al., 2012; José et al., 2007
	MOP2: Achieved overall cleaner or greener production/manufacturing system (such as proper coolant use, chip handling system, reduction of toxic/hazardous/harmful materials etc.)	Toke et al., 2012; Sambasivan et al., 2013; Diaz-Elsayed et al., 2013
	MOP3: Reduction of energy consumption	Sambasivan et al., 2013; Dong et al., 2013; Oda et al., 2012
	MOP4: Reduction of raw material consumption	Toke et al., 2012; Sambasivan et al., 2013; Pereira and Benedetti, 2013
	MOP5: Reduction of water consumption	Sambasivan et al., 2013; Coelho and Campos, 2014; Rezaei et al., 2010
	MOP6: Reduction of wastes/solid wastes/wastewater by recycling or controlling process through lean manufacturing/just-in-time (JIT)	Toke et al., 2012; Setiawati et al., 2013; Sambasivan et al., 2013
Non-Manufacturing based Operational Performance (NOP)	NOP1: Sale of scraps/wastes/excess materials/inventory	Kahn, 1985; Jaber and Saadany, 2009; Mauthoor et al., in press
	NOP2: Rating of customer satisfaction on green products (such as safety, energy efficiency etc.)	Toke et al., 2012; Sambasivan et al., 2013; Tseng and Hung, 2013
	NOP3: Approach of environmental auditing of suppliers with questionnaire to select green suppliers, mentioning environmental requirements like product testing report, bill of material, ISO 14001 certification in order to achieve green purchasing	Jabbour et al., 2013; Toke et al., 2012; Sambasivan et al., 2013; Buyukozkan and Cifci, 2012
	NOP4: Adoption of green transportation by using fuel efficient/environmentally friendly transportation system	Toke et al., 2012; Sambasivan et al., 2013; Lin et al., 2014
	NOP5: Adoption of green packaging (use of environmentally friendly materials, reuse/reverse logistics practice, consideration of less weight etc.)	Toke et al., 2012; Zhang and Green, 2012; Silva et al., 2013; Ramos et al., in press
	NOP6: Societal concern for protection of natural environment such as green disposal, plantation of trees etc.	Toke et al., 2012; Jaber and Saadany, 2009; Padhan et al., 2013; Silva et al., 2013
Financial Performance (FP)	FP1: Increased revenue/turnover	Toke et al., 2012
	FP2: Increased profit/reduction of production cost	Setiawati et al., 2013; Endrikat et al., in press
	FP3: Increased return on equity and cash-flow	Toke et al., 2012

Appendix 2. List of statistical terms/items used in research method and data collection

Sl no.	Terms/items	Expression of terms/items
1	Structural Equation Modelling	Statistical technique for testing and estimating causal relations between latent or unobserved variables allowing both confirmatory (theory testing) and exploratory modelling (theory development)
2	Fit	Refers to the ability of a model to reproduce the data (usually the variance-covariance matrix); a good-fitting model is one that is reasonably consistent with the data and so does not necessarily require respectification A good-fitting model is not necessarily a valid model, thus parameter estimates must be carefully examined to determine whether the model is reasonable as well as fit statistics; conversely, it should be noted that a model all of whose parameters are statistically significant may be from a poor fitting model
3	Maximum likelihood	Produces parameter estimates that are the most likely to have produced the observed correlations, if the sample is from a multivariate normal population
4	Little's Missing Completely at Random (MCAR) Test	Checks whether the missing data are in MCAR i.e. observed values of dependent variable are a truly random sample of all values of dependent variable, with no underlying process that lends bias to the observed data; p-value should be less than 0.05
5	p-value	In statistical hypothesis testing, the p-value is the probability of obtaining a test statistic at least as extreme as the one that was observed, assuming that the null hypothesis is true; if p-value is lesser than the default significance level of 0.05, then the null hypothesis is rejected
6	Varimax method	Rotates (referred to as orthogonal rotation) the axis such that the two vertices remain 90° (perpendicular) to each other assuming uncorrelated factors
7	Loadings	Expresses the correlation of the item with the factor while the square of this factor loading indicates the proportion of variance shared by the item with the factor
8	Communalities (c^2)	Proportion of the variance of an item that is accounted for by the common factors in a factor analysis leading to find out the unique variance of an item given by $1 - c^2$ (which is equal to item specific variance + item error variance or random error)
9	Ordinary Least Square (OLS) or Linear Least Square (LLS)	Statistical technique that uses sample data to estimate the true population relationship between two variables leading to solve the unknown parameters in a linear regression model (LRM); LRM relates a dependent/regressand/output variable with one or more independent/regressed/input variables
10	Coefficient of Determination (R^2)	Defined as a ratio of explained (independent) variance to the total variance of the dependent variable and expressed as follows where SSR is the Sum of Squared Residuals and TSS is the Total Sum of Squares for the dependent variable $R^2 = 1 - \frac{SSR}{TSS}$
11	Cross-loadings	Indicate how strongly each item loads on each other factor; there should be a gap of at least 0.2 between primary and cross-loadings
12	Absolute fit measures	Measures how well the correlation/covariance of the hypothesized model fits correlation/covariance of the actual or observed data based on discrepancies or matrix of residuals, Degrees of Freedom (DoF) and sample size; absolute fit index presumes that the best fitting model has a fit of zero determining how far the model is from perfect fit (i.e. measure of badness/bigger is worse)
13	t-value	t-statistic is given by the mean difference divided by the standard error; can be interpreted as how many standard errors away a mean from another value; t-value considers or takes into account sample sizes

Appendix 3

Appendix 3A
Result of the PCA for EP.

Variables	Load	Communalities
EP1	0.696	0.639
EP2	0.589	0.589
EP5	0.622	0.672
EP6	0.776	0.602
EP7	0.704	0.530
EP9	0.797	0.717
EP10	0.848	0.729
EP11	0.814	0.781

Appendix 3B
Result of the PCA for MOP.

Variables	Load	Communalities
MOP3	0.866	0.751
MOP4	0.816	0.666
MOP5	0.796	0.633
MOP6	0.725	0.525

Appendix 3C
Result of the PCA for NOP.

Variables	Load	Communalities
NOP2	0.779	0.607
NOP3	0.722	0.522
NOP4	0.834	0.695
NOP5	0.761	0.578
NOP6	0.711	0.506

Appendix 3D
. Result of the PCA for FP.

Variables	Load	Communalities
FP1	0.907	0.823
FP2	0.850	0.722
FP3	0.771	0.595

Appendix 3E
Pearson's correlation matrix for EP.

	EP1	EP2	EP5	EP6	EP7	EP9	EP10	EP11
EP1	1							
EP2	0.417[a]	1						
EP5	0.573[a]	0.396[a]	1					
EP6	0.382[a]	0.493[a]	0.368[a]	1				
EP7	0.414[a]	0.156[a]	0.322[a]	0.453[a]	1			
EP9	0.458[a]	0.248[a]	0.253[a]	0.563[a]	0.595[a]	1		
EP10	0.524[a]	0.261[a]	0.453[a]	0.632[a]	0.563[a]	0.656[a]	1	
EP11	0.460[a]	0.195[a]	0.217[a]	0.588[a]	0.600[a]	0.707[a]	0.704[a]	1

[a] Correlation is significant at the 0.01 level (2-tailed).

Appendix 3F
Pearson's correlation matrix for MOP.

	MOP3	MOP4	MOP5	MOP6
MOP3	1			
MOP4	0.683[a]	1		
MOP5	0.612[a]	0.605[a]	1	
MOP6	0.610[a]	0.484[a]	0.427[a]	1

[a] Correlation is significant at the 0.01 level (2-tailed).

Appendix 3G
Pearson's correlation matrix for NOP.

	NOP2	NOP3	NOP4	NOP5	NOP6
NOP2	1				
NOP3	0.479[a]	1			
NOP4	0.593[a]	0.514[a]	1		
NOP5	0.489[a]	0.407[a]	0.570[a]	1	
NOP6	0.475[a]	0.421[a]	0.519[a]	0.483[a]	1

[a] Correlation is significant at the 0.01 level (2-tailed).

Appendix 3H
Pearson's correlation matrix for FP.

	FP1	FP2	FP3
FP1	1		
FP2	0.703[a]	1	
FP3	0.567[a]	0.429[a]	1

[a] Correlation is significant at the 0.01 level (2-tailed).

Appendix 3I
Descriptive statistics for EP.

Variables	Average	Standard deviation
EP1	3.79	0.834
EP2	3.80	0.844
EP5	4.48	0.683
EP6	3.53	0.801
EP7	3.89	0.872
EP9	3.08	0.935
EP10	3.02	1.073
EP11	3.41	1.009

Appendix 3J
Descriptive statistics for MOP.

Variables	Average	Standard deviation
MOP3	3.52	1.009
MOP4	3.00	1.018
MOP5	3.10	0.897
MOP6	4.08	0.813

Appendix 3K
Descriptive statistics for NOP.

Variables	Average	Standard deviation
NOP2	2.29	0.833
NOP3	2.32	0.690
NOP4	2.54	0.859
NOP5	2.88	0.665
NOP6	3.41	0.864

Appendix 3L
Descriptive Statistics for FP.

Variables	Average	Standard deviation
FP1	3.49	0.887
FP2	3.86	0.793
FP3	3.66	0.840

References

Arimura, T.H., Darnall, N., Katayama, H., 2011. Is ISO 14001 a gateway to more advanced voluntary action? The case of green supply chain management. J. Environ. Econ. Manag. 61, 170–182.
Armstrong, J.S., Overton, T.S., 1977. Estimating non response bias in mail surveys. J. Mark. Res. 14 (3), 396–402.
Baud, I., Dhanalakshmi, R., 2007. Governance in urban environmental management: comparing accountability and performance in multi-stakeholder arrangements in South India. Cities 24 (2), 133–147.
Binder, S., Neumayer, E., October 2005. Environmental pressure group strength and air pollution: an empirical analysis. Ecol. Econ. 55 (4), 527–538.
Burke, S., Gaughran, W.F., 2006. Intelligent environmental management for SMEs in manufacturing. Robot. CIM-Int. Manuf. 22, 566–575.
Business Innovation and Skills (BIS), 2010. Manufacturing in the UK: an Economic Analysis of the Sector.
Butler, T., 2011. Compliance with institutional imperatives on environmental sustainability: building theory on the role of green IS. J. Strateg. Inf. Syst. 20, 6–26.
Buyukozkan, G., Cifci, G., 2012. A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers. Expert Syst. Appl. 39, 3000–3011.
Casadesús, M., Marimon, F., Heras, I., 2008. ISO 14001 diffusion after the success of the ISO 9001 model. J. Clean. Prod. 16 (16), 1741–1754.
Changhong, C., Bingyan, W., Qingyan, F., Green, C., Streets, D.G., 2006. Reductions in emissions of local air pollutants and co-benefits of Chinese energy policy: a Shanghai case study. Energy Policy 34 (6), 754–762.
Choi, A.C.K., Kaebernick, H., Lai, W.H., 1997. Manufacturing processes modelling for environmental impact assessment. J. Mater. Process Tech. 70, 231–238.
Chung, C.J., Wee, H.M., 2011. Short life-cycle deteriorating product remanufacturing in a green supply chain inventory control system. Int. J. Prod. Econ. 129, 195–203.
Claver, E., López, M.D., Molina, J.F., Tarí, J.J., 2007. Environmental management and firm performance: a case study. J. Environ. Manage. 84, 606–619.
Coelho, B., Campos, A., 2014. Efficiency achievement in water supply systems. Renew. Sustain. Energy Rev. 30, 59–84.
Cong, Y., Freedman, M., 2011. Corporate governance and environmental performance and disclosures. Adv. Acc. 27, 223–232.
Curkovic, S., 2003. Environmentally responsible manufacturing: the development and validation of a measurement model. Eur. J. Oper. Res. 146, 130–155.
Dangelico, R.M., Pontrandolfo, P., 2010. From green product definitions and classifications to the green option matrix. J. Clean. Prod. 18, 1608–1628.
Diaz-Elsayed, N., Jondral, A., Greinacher, S., Dornfeld, D., Lanza, G., 2013. Assessment of lean and green strategies by simulation of manufacturing systems in discrete production environments. CIRP Ann. Manuf. Techn. 62 (1), 475–478.
Dong, C., Haung, G.H., Cai, Y.P., Liu, Y., 2013. Robust planning of energy management systems with environmental and constraint-conservative considerations under multiple uncertainties. Energ. Convers. Manage. 65, 471–486.
Endrikat, J., Guenther, E., Hoppe, H., 2014. Making sense of conflicting empirical findings: a meta-analytic review of the relationship between corporate environmental and financial performance. Eur. Manage J. (in press), Corrected Proof, Available online 13 January 2014.
Foltz, C.B., 2008. Why users (fail to) read computer usage policies. Ind. Manage. Data Syst. 108 (6), 701–712.
González-Benito, J., González-Benito, Ó., 2005. Environmental proactivity and business performance: an empirical analysis. Omega 33, 1–15.
Hair, J.F., Ringle, C.M., Sarstedt, M., 2011. PLS-SEM: indeed a silver bullet. J. Mark. Theory Pract. 19 (2), 139–151.
Hon, K.K.B., Xu, S., 2007. Impact of product life cycle on manufacturing systems reconfiguration. CIRP Ann. Manuf. Techn. 56 (1), 455–458.

Hui, I.K., Chan, A.H.S., Pun, K.F., 2001. A study of the environmental management system implementation practices. J. Clean. Prod. 9, 269–276.
Indian Brand Equity Foundation (IBEF), 2013. Indian Manufacturing: Overview and Prospects.
Inter-countries Research for Manufacturing Advancement (IRMA), 2009. Analysis of the UK Manufacturing Engineering Sector.
Iwata, H., Okada, K., 2011. How does environmental performance affect financial performance? Evidence from Japanese manufacturing firms. Ecol. Econ. 70, 1691–1700.
Jabbour, C.J.C., Jabbour, A.B.L.S., Govindan, K., Teixeira, A.A., Freitas, W.R.S., 2013. Environmental management and operational performance in automotive companies in Brazil: the role of human resource management and lean manufacturing. J. Clean. Prod. 47, 129–140.
Jaber, M.Y., Saadany, A.M.A.E., 2009. The production, remanufacture and waste disposal model with lost sales. Int. J. Prod. Econ. 120 (1), 115–124.
Jayal, A.D., Badurdeen, F., Dillon Jr., O.W., Jawahir, I.S., 2010. Sustainable manufacturing: modeling and optimization challenges at the product, process and system levels. CIRP J. Manuf. Sci. Techn. 2, 144–152.
José, R.S., Pérez, J.L., González, R.M., 2007. An operational real-time air quality modelling system for industrial plants. Environ. Modell. Softw. 22 (3), 297–307.
Joung, C.B., Carrell, J., Sarkara, P., Fenga, S.C., 2012. Categorization of indicators for sustainable manufacturing. Ecol. Indic. 24, 148–157.
Kahn, W., 1985. Supply/demand and the pricing of scrap materials. Conserv. Recycl. 8 (3–4), 393–398.
Kapila, R.V., Chalmers, H., Haszeldine, S., Leach, M., 2011. CCS prospects in India: results from an expert stakeholder survey. Energy Procedia 4, 6280–6287.
Kenny, D.A., 2014. Measuring Model Fit. http://davidakenny.net/cm/fit.htm (accessed 20.03.14.).
Kline, R.B., 2005. Principles and Practice of Structural Equation Modeling. Guilford, New York.
Kneller, R., Manderson, E., 2012. Environmental regulations and innovation activity in UK manufacturing industries. Resour. Energ. Econ. 34 (2), 211–235.
Knight, P., Jenkins, J.O., 2009. Adopting and applying eco-design techniques: a practitioners perspective. J. Clean. Prod. 17 (5), 549–558.
Kumar, R., Pal, P., 2013a. Turning hazardous waste into value-added products: production and characterization of struvite from ammoniacal waste with new approaches. J. Clean. Prod. 43, 59–70.
Kumar, R., Pal, P., 2013b. A membrane-integrated advanced scheme for treatment of industrial wastewater: dynamic modeling towards scale up. Chemosphere 92 (10), 1375–1382.
Kuramochi, T., Ramírez, A., Turkenburg, W., Faaij, A., 2012. Effect of CO_2 capture on the emissions of air pollutants from industrial processes. Int. J. Greenh. Gas. Con. 10, 310–328.
Lannelongue, G., González-Benito, J., 2012. Opportunism and environmental management systems: certification as a smokescreen for stakeholders. Ecol. Econ. 82, 11–22.
Large, R.O., Thomsen, C.G., 2011. Drivers of green supply management performance: evidence from Germany. J. Purch. Supply Manag. 17, 176–184.
Lin, C.K.L., Ho, G.T.S., Ng, T.W., 2014. A genetic algorithm-based optimization model for supporting green transportation operations. Expert Syst. Appl. 41 (7), 3284–3296.
Ma, S., Zhang, S., Chen, Y., Zheng, H., 2013. Design and realization of a major environmental risk source management system. Procedia Environ. Sci. 18, 372–376.
Mandal, U.K., Sarkar, B., 2012. An exploratory analysis of intelligent manufacturing system (Ims) under fuzzy utopian environment. IOSR J. Eng. 2 (8), 129–140.
Marshall, N.A., Park, S., Howden, S.M., Dowd, A.B., Jakku, E.S., 2013. Climate change awareness is associated with enhanced adaptive capacity. Agric. Syst. 117, 30–34.
Mauthoor, S., Mohee, R., Kowlesser, P., 2014. An assessment on the recycling opportunities of wastes emanating from scrap metal processing in Mauritius. Waste Manage. 34 (10), 1800–1805.
Meyers, L.S., Gamst, G.C., Guarino, A.J., 2005. Applied Multivariate Research: Design and Interpretation.
Murillo-Luna, J.L., Garcés-Ayerbe, C., Rivera-Torres, P., 2011. Barriers to the adoption of proactive environmental strategies. J. Clean. Prod. 19, 1417–1425.
National Statistics, 2007. UK Standard Industrial Classification of Economic Activities 2007 Structure and Explanatory Notes.
Newton, T., Harte, G., 1997. Green business: Technicist Kitsch? J. Manage. Stud. 34 (1), 75–98.
Oda, Y., Kawamura, Y., Fujishima, M., 2012. Energy consumption reduction by machining process improvement. Procedia CIRP 4, 120–124.
Padhan, R.K., Gupta, A.A., Badoni, R.P., Bhatnagar, A.K., 2013. Poly (ethylene terephthalate) waste derived chemicals as an antistripping additive for bitumen – an environment friendly approach for disposal of environmentally hazardous material. Polym. Degrad. Stabil. 98 (12), 2592–2601.
Pan, L.J., Xie, Y.B., Li, W., 2013. An analysis of emission reduction of chief air pollutants and greenhouse gases in Beijing based on the LEAP model. Procedia Environ. Sci. 18, 347–352.
Pereira, T., Benedetti, M.M., 2013. A model for raw material management as a response to local and global environmental constraints. Quatern. Int. 318, 19–32.
Pizer, W.A., Morgenstern, R., Shih, J.S., 2011. The performance of industrial sector voluntary climate programs: climate wise and 1605(b). Energy Policy 39, 7907–7916.
Planning Commission, 2013. The Manufacturing Plan, Strategies for Accelerating Growth of Manufacturing in India in the 12th Five Year Plan and Beyond. Government of India.
Porter, M., Linde, C., 1995. Towards a new conception of the environmental competitiveness relationship. J. Econ. Perspect. 9 (4), 97–118.
Ramos, T.R.P., Gomes, M.I., Barbosa-Póvoa, A.P., 2013. Planning a sustainable reverse logistics system: balancing costs with environmental and social concerns. Omega (in press), Corrected Proof, Available online 12 December 2013.
Rezaei, E., Shafiei, S., Abdollahnezhad, A., 2010. Reducing water consumption of an industrial plant cooling unit using hybrid cooling tower. Energ. Convers. Manage. 51 (2), 311–319.
Ricoh Group Sustainability Report (Environment), 2007. http://www.ricoh.com/environment/report/pdf2007/all.pdf (dated 7th May, 2013).
Sambasivan, M., Saiku, M., Bah, S.M., Ho, Jo-Ann H., 2013. Making the case for operating "Green": impact of environmental proactivity on multiple performance outcomes of Malaysian firms. J. Clean. Prod. 42, 69–82.
Sarkis, J., 1995. Manufacturing strategy and environmental consciousness. Technovation 15 (2), 79–97.
Setiawati, E., Notodarmojo, S., Soewondo, P., Effendi, A.J., Otok, B.W., 2013. Infrastructure development strategy for sustainable wastewater system by using SEM method (Case study Setiabudi and Tebet Districts, South Jakarta). Procedia Environ. Sci. 17, 685–692.
Shapira, P., Gök, A., Klochikhin, E., Sensier, M., 2014. Probing "green" industry enterprises in the UK: a new identification approach. Technol. Forecast Soc. 85, 93–104.
Silva, D.A.L., Renó, G.W.S., Sevegnani, G., Sevegnani, T.B., Truzzi, O.M.S., 2013. Comparison of disposable and returnable packaging: a case study of reverse logistics in Brazil. J. Clean. Prod. 47, 377–387.
Smith, S., Yen, C.-C., 2010. Green product design through product modularization using atomic theory. Robot. CIM-Int. Manuf. 26, 790–798.
Sueyoshi, T., Goto, M., 2009. Can environmental investment and expenditure enhance financial performance of US electric utility firms under the clean air act amendment of 1990? Energy Policy 37 (11), 4819–4826.
Sueyoshi, T., Goto, M., 2010. Measurement of a linkage among environmental, operational, and financial performance in Japanese manufacturing firms: a use of data envelopment analysis with strong complementary slackness condition. Eur. J. Oper. Res. 207, 1742–1753.
Swain, A., July 2006. Climate Change Connection. Winnipeg, Manitoba, Canada, Version 1 (dated 7th May, 2013). http://www.climatechangeconnection.org/resources/documents/business_guide.pdf.
Terziovski, M., Power, D., Sohal, A.S., 2003. The longitudinal effects of the ISO 9000 certification process on business performance. Eur. J. Oper. Res. 146 (3), 580–595.
Testa, F., Rizzi, F., Daddi, T., Gusmerotti, N.M., Frey, M., Iraldo, F., 2014. EMAS and ISO 14001: the differences in effectively improving environmental performance. J. Clean. Prod. 68, 165–173.
Toke, L.K., Gupta, R.C., Dandekar, M., 2012. An empirical study of green supply chain management in Indian perspective. Int. J. Appl. Sci. Eng. Res. 1 (2), 372–383.
Tonjes, D.J., Mallikarjun, S., 2013. Cost effectiveness of recycling: a systems model. Waste Manage. 33 (11), 2548–2556.
Tseng, S.-C., Hung, S.-W., 2013. A framework identifying the gaps between customers' expectations and their perceptions in green products. J. Clean. Prod. 59, 174–184.
UK and India Partnership in Advanced Manufacturing Research Challenges, 2012. http://www.epsrc.ac.uk/files/funding/calls/2012/uk-india-partnership-in-advanced-manufacturing-research-challenges-call-document/(dated 8th June, 2013).
Vachon, S., Klassen, R.D., 2008. Environmental management and manufacturing performance: the role of collaboration in the supply chain. Int. J. Prod. Econ. 111, 299–315.
Walley, N., Whitehead, B., 1994. It's not easy being green. Harv. Bus. Rev. 46–52. May June.
Wang, W.-K., Lu, W.-M., Wang, S.-W., 2014. The impact of environmental expenditures on performance in the U.S. chemical industry. J. Clean. Prod. 64, 447–456.
Wetzels, M., Odekerken-Schroder, G., Oppen, C.V., 2009. Using PLS path modeling for assessing hierarchical construct models: guidelines and empirical illustration. MIS Quart. 33 (1), 177–195.
Wisner, P.S., Epstein, M.J., Bagozzi, R.P., 2010. Environmental proactivity and performance. Adv. Environ. Acc. Manage. 4, 105–127.
Wold, H., 1985. Partial least squares in S Kotz, N L Johnson (eds.). Enc. Stat. Sci. 6, 581–591.
Zhang, G., Green, Z., 2012. Packaging management of logistics enterprises. Phys. Procedia 24 (Part B), 900–905.
Zhao, K.R., Quan, D.Y., Yang, D.Y., Yang, J., Lin, K., 2010. A system for identifying and analyzing environmental accident risk sources. Procedia Environ. Sci. 2, 1413–1421.
Zhu, J.Y., Deshmukh, A., 2003. Application of Bayesian decision networks to life cycle engineering in green design and manufacturing. Eng. Appl. Artif. Intel. 16, 91–103.
Zhu, Q., Cordeiro, J., Sarkis, J., 2013. Institutional pressures, dynamic capabilities and environmental management systems: investigating the ISO 9000 – environmental management system implementation linkage. J. Environ. Manage. 114, 232–242.