An Environmental Uncertainty-based Diagnostic Reference Tool for Evaluating the Performance of Supply Chain Value Streams

David Gallear, Abby Ghobadian, Rose Li, Nicholas O'Regan, Paul Childerhouse and Mohamed Naim

Dr David Gallear
Brunel Business School
Brunel University
Uxbridge UB8 3PH
United Kingdom
Email: David.Gallear@brunel.ac.uk

Professor Abby Ghobadian
Henley Business School
Greenlands
Henley-on-Thames
Oxfordshire, RG9 3AU
United Kingdom
Email: abby.ghobadian@henley.reading.ac.uk

Rose Li
University of Oxford Department of Education
15 Norham Gardens
Oxford OX2 6PY
United Kingdom
Email: Yanhong.li@education.ox.ac.uk

Professor Nicholas O'Regan
Bristol Business School
University of the West of England
Coldharbour Lane
Bristol BS16 1QY
United Kingdom
Email: Nicholas.O'Regan@uwe.ac.uk
Tel: +44 (0) 117 328 3735

Professor Paul Childerhouse
Massey University, Private Bag 11 222
Palmerston North, 4442
New Zealand
Email: p.h.j.childerhouse@massey.ac.nz

Professor Mohamed Naim
Cardiff Business School
Aberconway Building
Colum Drive
Cardiff CF10 3EU
Email: NaimMM@cardiff.ac.uk

An Environmental Uncertainty-based Diagnostic Reference Tool for Evaluating the Performance of Supply Chain Value Streams

Abstract

This research has responded to the need for diagnostic reference tools explicitly linking the influence of environmental uncertainty and performance within the supply chain. Uncertainty is a key factor influencing performance and an important measure of the operating environment. We develop and demonstrate a novel reference methodology based on the data envelopment analysis (DEA) for examining the performance of value streams within the supply chain with specific reference to the level of environmental uncertainty they face. In this paper, using real industrial data, 20 product supply value streams within the European automotive industry sector are evaluated. Two are found to be efficient. The peer reference groups for the underperforming value streams are identified and numerical improvement targets are derived. The paper demonstrates how DEA can be used to guide supply chain improvement efforts through role-model identification and target setting, in a way that recognises the multiple dimensions/outcomes of the supply chain process and the influence of its environmental conditions. We have facilitated the contextualisation of environmental uncertainty and its incorporation into a specific diagnostic reference tool.

Keywords: Diagnostic reference tool; data envelopment analysis; supply chain; performance measurement; environmental uncertainty; contingency theory

1. Introduction

Over the past few decades globalisation coupled with hyper competition has pushed supply chain management (SCM) to the forefront of research and practice agendas (e.g. Harland, 1996; Storey *et al.*, 2006; Christopher, 2011). A supply chain consists of a geographically dispersed network of actors that transform raw materials into distributed products (Bowersox *et al.*, 1999). The coordination, control, and improvement of such a complex network of activity offers a major challenge to managers. A properly designed performance measurement system is the cornerstone of effective coordination, control and enhanced competitiveness, and hence the growing attention to supply chain performance measurement issues (Gunasekaran *et al.*, 2004). The result is a glut of performance measures (Beamon, 1999), many of which have been criticised principally because they: (a) fail to reflect the multiple dimensions/goals of business units within the supply chain (Bytheway, 1995; Beamon, 1999), and (b) ignore the factors that are beyond the control of management, such as uncertainty (Beamon, 1999).

Data envelopment analysis (DEA) offers a solution to the shortcomings highlighted above. First, the technique is highly versatile enabling analysts to use ordinal, discrete, interval and ratio variables side by side to construct a performance model. As such, factors frequently measured using ordinal variables such as environmental uncertainty can be included in the analysis. Second, it can contextualise and make allowances for the factors that are outside the control of management but affect the performance of business units within the supply chain. Third, it can help management to establish informed improvement targets (Charnes *et al.*, 1994; Liu *et al.*, 2000; Saranga and Moser, 2010).

This paper demonstrates a novel application of how the DEA technique can be used to facilitate the development of a diagnostic reference tool to analyse the supply chain performance of product value streams (business units) operating within a supply chain network. Moreover, it also demonstrates how the tool can be used to guide management's efforts to improve the units' performance through role-model identification and target setting, in a way that recognises the multiple dimensions/outcomes of the supply chain process and the influence of its environmental conditions.

Environmental uncertainties have a major impact on the performance of the supply chain and on managerial decisions, and the ability to align the organisation with the demands of the external environment is an important source of competiveness. The performance management technique we present enables managers to establish how well their product value stream is aligned with the uncertainties of the external environment in comparison with the best aligned value stream. By applying this technique, they can discriminate between the most efficient and less efficient product value streams. It enables not only comparison of like with like, but allows managers to pinpoint weaknesses and set appropriate improvement targets. Moreover, managers can identify suitable role models (value streams other than those on the best performing frontier) and systematically improve target levels. The flexibility to select an appropriate role model is of significant benefit.

Environmental *uncertainty* in this application is derived from the examination of supply-side factors, demand-side factors, internal process factors and control factors, across the linkages of product value streams extending upstream from a focal business unit to the first-tier suppliers, and downstream to the first-tier customers. As such, the model incorporates data spanning the focal business units' immediate supply network (Slack *et al.*, 2004). Real industrial data is used, extracted from a survey conducted within the European automobile supply chain.

The choice of uncertainty as the input variable in the measurement model is predicated on the co-alignment and contingency theories of management. Both theories play an important role in organisational research (Carroll, 1993; Johnson *et al.*, 2002). In the context of the supply chain, Van der Vorst and Beulens (2002) pointed out that the literature unanimously recognises that uncertainties in supply, process and demand have a major impact on the manufacturing function. Davis's (1993) analysis highlighted the presence of uncertainty at all levels within a global supply chain from raw materials acquisition to finished product demand (Talluri and Baker, 2002). Van der Vorst and Beulens (2002) argued that uncertainty propagates throughout the supply chain and leads to inefficient processing and non-value-adding activities. As such, uncertain environments bring immense pressure on all organisations to make 'carefully considered effective decisions' (Koutsoukis *et al.*, 2000).

The motivation for this research stems firstly from the increasing recognition within the SCM literature of the critical influence of uncertainty on the efficiency, effectiveness and flexibility of supply chains (Wilding, 1998; Koutsoukis *et al.*, 2000; Van der Vorst and Beulens, 2002; Lockamy *et al.*, 2008), secondly from the paucity of empirical research examining the influence of uncertainty on supply chain performance, and thirdly from the perceived advantages offered by the DEA technique for developing diagnostic reference tools for comparative performance assessment (Talluri and Baker, 2002; Saranga and Moser, 2010).

The paper is organised as follows. First, a discussion of performance measurement within the supply chain is presented, followed by an explanation of DEA's general principles and an examination of relevant past applications. The data sources and research design are then discussed, followed by the application of the DEA model to a sample of firms operating within the European automobile industry. Finally, managerial implications of the use of the diagnostic reference model, conclusions and suggested avenues of future research are discussed.

2. Supply chain strategy and performance evaluation

The supply chain management concept and cycle time compression stem from a shift in predominance of price competition to simultaneously competing on a broad range of factors (Hewitt, 1994; Godsell *et al.*, 2011). Maximising the value added to products and satisfying customers have become more and more important in addition to inventory elimination and cost reduction. This prompted Hewitt (1994) to suggest that an efficient and effective supply chain management strategy ought to address value maximisation, process integration, and responsiveness/cycle time reduction simultaneously. Bytheway (1995) extended this argument by suggesting that the following three broad types of supply chain strategies were open to organisations: efficiency, effectiveness and evolution-based strategies. The focus of an efficiency strategy is on improving productivity, reducing cost and increasing the profit margin. An effectiveness strategy, on the other hand, is concerned with quality, service excellence and image. An evolution strategy focuses on developing the organisation's ability to respond to changes taking place in its operating environment. According to Bytheway (1995) hitherto efficiency type strategies have been the most prevalent, however, these strategies work best in stable and mature markets. In reality, not all markets are mature and, more importantly, most markets are unstable. The greater environmental turbulence means that organisations increasingly have to pursue all of the three supply chain strategies simultaneously. Pursuing a single supply chain strategy carries several risks. First, it may result in a misalignment with the operating environment. Second, it may result in a misalignment with the organisation's strategic goals. In either case the organisation's risk of failure increases. Bytheway (1995) went on to argue that the supply chain evaluation system should enable management to understand their business's strategic position and what can be improved in the business, thus, he proposed a supply chain performance measurement model consisting of the following three broad dimensions: efficiency, effectiveness, and market responsiveness. Li and O'Brien (1999) also recognised multiple goals/dimensions of supply chains and suggested that profitability, flexibility, reliability and waste limitation are the four important aspects of SCM. Akyuz and Erkan (2010) and Beamon (1999) conducted a comprehensive review of supply chain performance measurement models, and concluded that the current models suffered from the following limitations:

- focusing on cost as the primary measure of performance;
- reliance on a single, mainly economic oriented, supply chain performance measure;
- ignoring the interactions among different supply chain strategies; and
- ignoring the potential influence of uncertainty, which is outside management control but has a strong influence on supply chain performance.

Beamon (1999) proposed a framework for the measurement of supply chain performance comprising of three broad components critical to supply chain success: efficient use of resources, quality of products and service, and system flexibility. She further argued that an adequate supply chain measurement system must at least contain one measure from each of the three broad performance components, and moreover, that the measures used for representing each of the dimensions must be consistent with the organisation's strategic goals. Beamon's (1999) proposed model explicitly assumes that the three broad supply chain strategies identified by Bytheway (1995) and discussed earlier, are not mutually exclusive and that only a comprehensive system of measurement could show the effect of interactions between different supply chain strategies. A key issue for organisations is the weight to be attached to each of these strategies.

There is a broad consensus that process-driven analyses provide essential links between strategy, execution, and ultimate value creation (Melnyk *et al.*, 2004). The literature, while divided on specific measures, is more united on the desirable attributes of supply chain performance measures. These important attributes can be summarised as follows (Beamon, 1999; Borenstein *et al.*, 2004; Akyuz and Erkan, 2010):

(a) reliance on cost measures is insufficient and could be potentially misleading in a fast-changing and increasingly competitive environment;

(b) models ought to reflect a multiplicity of goals and outcomes – they should include quantitative and qualitative measures – furthermore, measures ought to reflect the strategic priorities of the organisation;

(c) the measurements used should take into account the effects of contexts or situation-related factors; and

(d) to enable management to control and plan, the performance/outcomes should be compared and contrasted against the best possible potential performance.

The above requirements increase the complexity of supply chain performance evaluation models. One of the biggest problems of using multiple measures is interpretation, because it is usual for different metrics to move in different directions. Moreover, it is also often difficult to combine different measures and construct a single index. For control and planning purposes the performance over one time period can be compared with:

- past performances of the organisation, that is to say temporal comparisons;
- the performance of different divisions of an organisation, that is to say internal cross-sectional performance; or
- the performance of different organisations, that is to say external cross-sectional performance.

These comparisons would be more meaningful if a robust single diagnostic measure could be established and the current performance (in temporal studies) or the performance of the division or organisation in cross-sectional studies could be compared with the most efficient performance that has occurred. Furthermore, it would be more useful to managers if they could identify the reasons for inefficiencies. The data envelopment analysis (DEA) technique discussed in the following sections can potentially address all the desirable attributes of a multi-goal supply chain diagnostic reference model and facilitate the development of a close to ideal performance index.

3. Data envelopment analysis (DEA) and its applications

DEA is a linear-programming-based method for assessing the relative performance of decision-making units (DMUs). It measures the relative efficiency of each DMU in comparison to other DMUs (Liu *et al.*, 2000). The method was initially proposed by Charnes *et al.* (1978) based on the definition of efficiency proposed by Farrell (1957): the ratio of attainable output to actual inputs. A distinctive feature of DEA, considered to be its primary advantage (Easton *et al.*, 2002; Cherchye *et al.*, 2008), is that it can establish a combined (or composite) index of overall performance thus facilitating easy comparison between decision-making units such as departments, organisations or supply chains. DEA converts multiple input and output measures of a DMU into a single comprehensive measure of efficiency, thus providing a measure by which one DMU can compare its performance, in relative terms, to other homogeneous DMUs (Easton *et al.*, 2002). It can also give information on the individual performance measurements that make up the aggregate score thus enabling the manager of a DMU to take action on specific measures, and as Easton *et al.* (2002) further explain, because both input and output measures are incorporated to provide a measure of efficiency (i.e. outputs/inputs) a more valid comparison between DMUs is provided.

According to Weber (1996), mathematically DEA starts by identifying an ‘efficient frontier’ from the observed inputs and outputs of the set of decision-making units under examination. Based on the notion of Pareto optimality, this efficient frontier is determined by the most efficient DMU(s) under study. A DMU is efficient if there is no other DMU (or combination of other DMUs) that can produce at least the same levels of all outputs, with less of some resource input and no more of any other. The relative efficiency of each DMU relative to this efficient frontier is then calculated (Weber, 1996).

The efficiency score for a DMU is defined as the total weighted score of outputs divided by the total weighted score of inputs. To avoid the potential difficulty in assigning these weights among various DMUs, the DEA technique computes weights that give the highest possible relative efficiency score to a DMU while keeping the efficiency scores of all DMUs less than or equal to one under the same set of weights (Liu *et al.*, 2000). It is this approach that ensures that all DMUs are evaluated on the basis of relative efficiency (Easton *et al.*, 2002). DEA’s total objectivity in the establishment of weights for the input and output measures is considered to be a further major benefit (Braglia and Petroni, 2000). The feedback potential of DEA, through the provision of helpful information to managers for use in improving performance, make it a valuable tool for enhancing the quality of decision making (Easton *et al.*, 2002). A further major advantage of the DEA technique is its versatility – it enables the analyst to use ordinal, discrete, interval and ratio variables side by side to construct a diagnostic model. Thus, factors such as environmental uncertainty measured in ordinal variables can be central in the analysis.

Arguably, one of the main benefits of using DEA over other PM tools that are used for informing managerial action (for example regression analysis or cost–benefit ratio analysis) is its ability to provide benchmarking DMUs and a peer reference group for inefficient DMUs (Yang *et al.*, 2011). The technique enables the analyst to construct an overall performance index from multiple input and output variables and identify the most efficient frontier. By identifying efficient DMUs, benchmarks of performance for inefficient DMUs are established for direct comparison, thus guiding managers' appreciation of how resources may be best directed for improvement. Furthermore, it can deal with many different inputs and outputs simultaneously and, by using the non-parametric approach, without prior knowledge of the function of inputs and outputs.

From its origins in the not-for-profit sector (Charnes *et al.*, 1981), the use and applications of DEA have expanded to the private/for-profit sectors (Easton *et al.*, 2002). Applications in the not-for-profit sector have included: healthcare/hospitals (Pina and Torres, 1992; Chilingerian, 1994), education (Knox Lovell *et al.*, 1994; Beasley, 1995) and governmental organisations (de Boer and Telgen, 1998) among others. DEA models have successfully been applied in the private/for-profit sector fields such as manufacturing (Ray and Kim, 1995; Xu *et al.*, 2009), retailing (Athanassopoulos, 1995; Vaz *et al.*, 2010), banking (Al-Faraj *et al.*, 1993; Pasiouras, 2008) and transport (Forsund and Hemaes, 1994) among others.

Since the early 1990s, the use of DEA in supply chain management-related situations has also expanded. For example, Talluri and Baker (2002) applied DEA to determining the optimal number of suppliers, manufacturers and distributors for supply chain network design. Sevkli *et al.* (2007) applied DEA for comparing suppliers of an appliance manufacturer in Turkey. The nature and utility of a range (non-exhaustive) of real-world empirical DEA applications in the supply chain management arena are presented in Table 1.

"take in Table 1"

This paper extends such applications. Its unique contributions lie in its application to value stream performance diagnosis within the supply chain and its incorporation of environmental uncertainty in the measurement model, neither of which have been covered in prior research.

4. An environmental uncertainty-based diagnostic tool

The single input, multiple output DEA evaluation model used in this study is based upon the Charnes–Cooper–Rhodes (CCR) ratio model (Charnes *et al*., 1978, 1994).
This is a well-established and extensively applied model, and as such its discussion and mathematical notation is limited in the main body of this paper. A description of the model as used in our analysis is presented in Appendix 1.The CCR model was chosen for its appropriateness to this application given its ability to establish a best-practice frontier based on best observed performance, and evaluate the efficiency of each decision-making unit (DMU) relative to this frontier. CCR remains one of the most frequently used DEA models in practical applications (Green and Cooks, 2004). It is recognised as one of the most

influential models by researchers (Seiford 1996), and has been successfully applied in many operations and supply chain performance studies (for example, Azadeh *et al*., 2007; Li and Dai, 2009; Azadi and Saen, 2011; Yang *et al.*, 2011). Furthermore, it is appropriate in applications, such as the present application, where there are no economies (or diseconomies) of scale present due to significant variations in the size of DMUs.

We deploy the diagnostic model to compare the performance of 20 product delivery value streams in the European car industry. In this manner, the DEA model measures the relative efficiency of each value stream based on multiple criteria when compared to the most efficient value streams under investigation. The data sources and rationale for the selection of the input and output variables are discussed in this section. The next section then demonstrates the application of the diagnostic model.

4.1 Data sources and research design

The primary data used in this application were drawn from the Quick Scan (QS) audit study (Childerhouse, 2002; Towill *et al.* 2002) carried out by a UK-based university research group. This choice was influenced by two important considerations. First, the purpose of the QS study was to collect information to assess and evaluate supply chain performance. More specifically it was to study the uncertainty and related factors capable of influencing the performance of supply chains. Thus, the information collected by the QS audits was highly relevant to the development of this diagnostic tool. Second, the organisations covered by the study sample were from the European automotive industry and thus the data set was homogenous. This eliminated potential variations in supply chain performance due to industrial contingencies, making direct comparison plausible. A detailed description of the Quick Scan methodology is beyond the scope of this paper. The reader is referred to

Childerhouse (2002) and Towill *et al.* (2002) for a full description of the procedure. Specifically, for this study the focal decision-making units (DMUs) to be evaluated and compared are (single echelon) business units representing product delivery processes from the European automotive industry sector. Data incorporated in the DEA model's input variable (discussed fully in the next section) are derived from the examination of the characteristics of (i) the supply-side linkage of each of the business units to their first-tier suppliers, and (ii) the demand-side linkage of each of the business units to their first-tier customers, in addition to the business unit's internal process and control factors. As such, the evaluation model incorporates data from beyond the boundaries of a single business unit echelon. The DMUs are referred to in this paper as (product delivery) value streams for accuracy. An organisation typically consists of a number of delivery value streams, and by focusing on a single delivery value stream we avoid aggregating environmental conditions that are likely to be different for different value streams. This approach helps us to avoid loss of important data and provides a more focused and meaningful reference model and analysis.

4.2 Selection of DEA variables

The selection of input and output variables plays a key role in the efficacy of the diagnostic model. The choice is influenced by the strategic goals of the supply chain, ease of defining the relevant variables, the ability to measure the selected variables at regular intervals, level of aggregation, ease of understanding, and cost/benefit trade-off of the measures involved. The model presented in this paper is based on the assumption that the goal of the supply chain is simultaneous improvement of its efficiency, effectiveness and flexibility. The variables selected for the model presented in this paper are given in Table 2.

"take in Table 2"

4.2.1 DEA input variable – environmental uncertainty

Traditionally, input in the operations management context is defined as the labour, material and capital cost. However, in the case of highly complex systems in a supply chain it is very difficult if not impossible to identify the labour, material and capital cost that is a direct input to a complex multistage process. On the other hand, as highlighted previously, many authors have identified uncertainty as a key factor influencing the efficiency, effectiveness and flexibility of the supply chain (Wilding, 1998; Koutsoukis *et al.*, 2000; Van der Vorst and Beulens, 2002; Lockamy *et al.*, 2008). Sabri and Beamon (2000) state that 'uncertainty is one of the most challenging but important problems in supply chain management', and the existing body of knowledge suggests that uncertainty is an important input to any supply chain performance measurement model. Christopher (2011) and Bowersox and Closs (1996) also point out that the performance of different supply chains and the decision-making units within them is influenced by the level of uncertainty they experience.

In this application, uncertainty is deliberately chosen as the sole input variable defining the reference model. The extant management literature suggests that the environment is a source of constraints, contingencies, problems and opportunities that affect the terms on which organisations transact business (Khandwalla, 1977; Mintzberg, 1979). As open systems, organisations need to adapt to the changing environment through changes in the way they transact business (Katz and Kahn, 1966; Lawrence, 1981). Environment is defined as the aggregate of factors that have an impact or the potential to have an impact on an organisation's functioning (Emery and Trist, 1965; Thompson, 1967). The choice of uncertainty as the sole input variable in the model is predicated on the co-alignment and contingency theories. Both co-alignment and contingency theory play an important role in organisational and operations management research (Hofer, 1975; Carroll, 1993; Johnson *et al.*, 2002).

The co-alignment theory suggests that the ability of an organisation to adapt to the changing environmental contingencies to 'fit' with the operating context is the key to survival and enhanced performance (Chandler, 1962; Jauch *et al.*, 1980; Lawrence, 1981; Yasai-Ardekani and Nystrom, 1996). The effectiveness of the adaptive response is dependent on aligning the response to the environmental circumstances faced by the organisation (Miles and Snow, 1978; Hambrick, 1983; Lee and Miller, 1996; Strandholm *et al*., 2004). Contingency theory suggests that managers play an active but limited role in the continuous process of adapting to the emerging contingencies (Thompson, 1967; Hofer, 1975; Grandori, 1984). Managers are viewed as a component of the total system that is technically constrained by the environment (Astley and Fombrun, 1983; Bourgeois, 1984). The focus of managerial decision making is not primarily choice, but on gathering correct information about changes in the environment and examining the consequences of alternative responses because strategic choice among contingencies are more consequential (Astley and Van de Ven, 1983). In other words, the key input to an organisational unit is provided by the environment and managers who respond appropriately are likely to achieve superior performance. As such, the uncertainty is an important measure of the operating environment and an input that managers need to react to. The nature of the reaction, to a large extent, determines the likelihood of organisational success.

Measuring uncertainty is not simple. Both Davis (1993) and Mason-Jones and Towill (1998) segmented supply chain uncertainties into four areas within the supply chain so that root-causes and methods for minimisation can be developed. The latter identify the four areas of:

value-adding process uncertainty, supply uncertainty, demand uncertainty and control (system) uncertainty.

The measure for the DEA input variable *uncertainty score* was the aggregate (sum) of four individual scores (each on a four point Likert scale) given for (i) supply-side uncertainty, (ii) demand-side uncertainty, (iii) process uncertainty and (iv) [system] control uncertainty. Accordingly, an *uncertainty score* of 16 represents the highest perceived value stream uncertainty, and an *uncertainty score* of one the lowest. Table 3 shows the simple questionnaire completed with respect to each value stream (Towill *et al.*, 1999, 2002; Childerhouse, 2002), and Appendix 2 presents the primary data collected and used for assessing uncertainty in the four supply chain areas during the QS audit investigations. Each QS audit involved multiple site visits to each value stream business unit by the QS team (a multidisciplinary team of researchers, site engineers and managers, and experts from the research partner). The questionnaire was completed by members of the QS team on the basis of the total information relating to uncertainty at their disposal. To ensure comparability, the questionnaires for all 20 value streams were activated only once all had been analysed, and where necessary the Likert scores were verified by cross-reference to detailed QS reports and re-visiting various data banks. The choice of a four point Likert scale was aimed at reducing any tendency to regress towards the mean, and instead to focus on strengths and weaknesses of individual value streams (Saunders *et al.*, 2002). In summary, the uncertainty score measure is an assessment of the environmental conditions in which the business is operating, and for the reasons stated previously it is the input variable in our diagnostic model.

“take in Table 3”

4.2.2 DEA output variables

The three output variables used in the diagnostic model are *profit margin*, *delivery window* and *schedule stability* (Table 2). These three variables were chosen, in the context of the European automobile industry, to reflect the three essential dimensions of supply chain strategies identified by Beamon (1999). Profit margin measures the efficient use of resources. Efficient resource management is critical to profitability (Beamon, 1999). Profit margin is a generally accepted performance measure and is used to measure efficient use of resources in this application because unlike other measures such as total cost of manufacturing and amount of obsolete inventory for example, it provides a more extensive representation of each value stream's resource performance. The measure for *profit margin* is price minus variable cost, divided by price. Delivery window is the measure of on-time delivery, a critical component in customer service. The measure for delivery window is the percentage of orders delivered by the value stream to the customer on or before the specified due date. Schedule stability is a measure of each value stream's flexibility. It is a measure of the value stream's achieved response to its changing requirements in terms of product volume, delivery and product mix. The measure of schedule stability is the percentage variation of the actual monthly schedule for the value-adding process against the planned monthly schedule. These measures were collected from the 20 value streams by the researchers while on their site visits to conduct the QS audits.

The output variables included in the model were chosen very carefully. For instance, one important variable, representing on-time delivery, was used to measure the quality of customer service dimension. The same applies to the measure of system flexibility. Schedule stability, the variable used in this study, is considered highly appropriate in this application since it measures the capability of each value stream system to meet its final monthly production schedule after the required volume, delivery and mix adjustments have been incorporated into the schedule. As such it is a measure of the value stream's achieved response (flexibility) to its changing requirements in terms of product volume, delivery and product mix.

Arguably it may be considered desirable to construct a diagnostic model containing a wider set of input and output measures. However, it is a requirement to restrict the numbers of variables utilised in the DEA model, since too many variables would result in loss of discrimination among value streams (Thanassoulis *et al.*, 1987). There is a need to strike a balance between the number of measures deployed and the discriminatory power of the DEA model. The set of output measures used here meets the requirement of any DEA-based analysis for robust measures whilst at the same time providing the power to discriminate. These output measures are in alignment with the overall supply chain strategy of the industry sector.

5. Diagnostic results and analysis

The original data set contained 25 value streams. Five value streams were discarded for the purposes of this analysis because they contained missing data, thus 20 value streams remained in the data set. All of the value streams were located in Europe, with the majority (12) in England, three in Germany and in Wales respectively, and two in Scotland. All of the value streams were from the automotive manufacturing sector and resided within the local supply network supplying automotive components or assemblies to larger original equipment manufacturers (OEMs). All of the value stream products were automotive components/assemblies and were primarily from the engine or braking system areas. The major value-adding processes represented by the value streams in the sample were machining and assembly; machining; automated/final assembly; heat treatment; forging; and distribution warehousing. Appendix 3 summarises the location, product types and major value-adding processes of the data set. The DEA results and analysis are presented in the following sections.

5.1 Overall value stream performance scores

For planning and control purposes, an important starting point when assessing value stream performance is to determine which value stream or value streams have achieved the best output results given the input. In our model, we need to identify which value streams have achieved the best output results (profit maximisation, high level of customer service and system flexibility) given the different degrees of uncertainty faced by the value streams. In the analysis that follows, DEA results for value stream six (VS6) are highlighted in order to illustrate the managerial interpretation.

The DEA programme identifies a group of value streams that performed optimally and assigns them a score of one. These value streams are then used to create a frontier, or data envelope, against which the performance of other value streams is assessed and compared. The value streams that produce less weighted output per weighted input than the best-performing value streams (the frontier) are considered technically inefficient. They are given a score of less than one, but greater than zero. The closer the DEA rating is to one, the closer the value stream is to the efficient frontier. The DEA ratings of overall performance for each value stream are shown in Table 4.

"take in Table 4"

The DEA analysis identified two out of 20 value streams – VS4 and VS17 – that lie on the efficient frontier. That is to say, they have performed most efficiently given the uncertainty conditions and were rated as 100 percent efficient relative to the other value streams in the sample. All other value streams, by comparison to the most efficient, are under performing given the uncertainty conditions. The DEA ratings of the other value streams ranged from a low of 0.1414 to a high of 0.7475. Value streams 18 and 19 have the poorest performance. In addition to the overall rating scores, DEA also provides management with further useful information that can be used to guide improvement of the performance of the value streams. Peer reference comparisons are discussed more fully in the next section. As shown in Table 4, value streams four and 17 have been identified (either jointly or solely) as the peer references for each of the value streams rated as inefficient. In the first instance therefore, value streams four and 17 could be further studied by management to reveal operating or management processes and practices that lead to improved performance.

5.2 Peer references for under-performing value streams

With respect to each of the inefficient value streams, DEA identifies its peer references. The peer references for each of the inefficient value streams are one or more of those that have an overall DEA performance rating of unity. The DEA calculation allows each value stream to choose values for the input variable and output variable weights that serve to show it in the best possible light. These weights render its peers relatively efficient. This makes the peers useful reference points because they have better performance in precisely the areas that the value stream chooses to emphasise (i.e. weight heavily) when compared with other value streams. As a result it is likely that there is a measure of agreement (explicit or implicit) between a value stream and its efficient peers on the relative values of the outcomes and the relative strength of the environmental influences on these outcomes. Thus, the efficient peers for each value stream can act as its role models in its effort to improve its performance.

Value stream six was found to have relative efficiency of 0.56 (Table 4). This means that relative to its efficient peers, the overall output level of VS6 is only 56 percent of its potential level. The efficient peers for VS6 are both VS4 and VS17. The performance of VS6 can now be contrasted with that of its efficient peers to see why it has attained a lower relative efficiency score.

Table 5 shows the original data for VS6 and its peer references VS4 and VS17. In order to make the comparison between the inefficient value stream and its efficient peers as clear as possible, the data have been scaled by the factor labelled ‘scale’. Thus, both inefficient VS6 and its efficient peer VS17 have been scaled so that their input levels are the same as the input level of efficient peer VS4. With the input level for all three value streams adjusted to the same amount (i.e. 6.0), a relatively simple comparison can now be performed on the outputs.

“take in Table 5”

Table 5 clearly shows that the efficient peers VS4 and VS17 perform better than VS6 when the scale data are compared. The data show that with the same input level as VS4 and VS17, almost all of the outputs of VS6 are significantly lower than those of VS4 and VS17. Compared with efficient peer VS17, VS6 has achieved significantly lower performance in both *delivery window* and *schedule stability*, although it has a marginally higher value in the case of *profit margin*. With reference to efficient peer VS17, given the uncertainty conditions, the expected performance of VS6 for *delivery window* is 13.09, however VS6’s actual relative performance is only 7.2. The scaled data in Table 5 show that compared with its efficient peer VS17, VS6 is only achieving 55 percent of VS17's performance level in *delivery window* and only 4.5 percent of VS17's performance level in *schedule stability* even though they would both be operating under the same level of environmental uncertainty. It is worth noting that although both VS4 and VS17 are peer references for VS6, it is reasonable to argue that VS4 is in fact a better role-model to VS6 than is VS17, because the output levels for VS4 are more challenging for VS6 to reach than those for VS17. Notice also, from Table 4, that VS4 is a peer reference to more inefficient value streams than VS17. On the other hand, the management of VS6 may choose to be more conservative in their improvement drive and hence select VS17 as the immediate role-model. On the basis of this analysis, we can conclude that as a strategic decision, the management of value stream six should concentrate on improving *schedule stability* in order to be as efficient as their efficient peers because this lag in performance compared with its efficient peers is the largest.

Contrasting low overall rating scores of value streams with their peers in this way can help reinforce the case that the inefficient value streams need to improve their performance. Yet an inefficient value stream can, of course, study and adopt operating practices of any other value stream regardless of whether it is one of its efficient peers. What makes the reference peers special is that they are efficient with the very value system that would show the inefficient value stream in the best light, and hence they are likely to offer operating practices and environmental comparability with those of the inefficient value stream. This is what makes them particularly suitable as role models, which the under-performing value stream can seek to emulate to improve its performance.

5.3 Setting targets for improvement

Apart from identifying peer references for the managers of inefficient value streams to study more closely, the DEA assessment also yields the target values of input and outputs that, in principle, the inefficient value stream ought to be able to achieve. These target values can be deduced directly from the optimal solution of model M1 (Appendix 1). However, they are more conveniently explained with reference to the optimal solution to the dual to model M1, which is designated as model M2 (Appendix 1).

Through the linear programming solution, one can obtain all the targets for each of the value streams. These are presented in Table 6. The targets indicate the best possible achievement for a value stream given its uncertainty condition. The data indicate that for at least 14 of the inefficient value streams there is considerable room for improvement, despite the demands of their operating environment. All efficient value streams have already attained the optimal performance for the data set, compared with the inefficient value streams. These efficient value streams are used as benchmarks to derive the goals for inefficient value streams. For instance, value stream six has only achieved 56.00 percent, 1.88 percent and 55.99 percent of its potential performance for *delivery window*, *schedule stability*, and *profit margin* respectively. In other words, given its current operating level of environmental uncertainty, this value stream can improve 44 percent, 98 percent and 44 percent in *delivery window*, *schedule stability* and *profit margin* respectively. Similarly, the management of value stream 10 know that given its current operating level of environmental uncertainty, it should be able to improve its performance in *delivery window*, *schedule stability* and *profit margin* respectively by as much as 27 percent, 25 percent and 59 percent respectively. In both cases therefore, there is significant room for improvement.

Targets such as those in Table 6 do not reflect any emphasis on improving a specific output of a value stream; they merely indicate the maximum pro rata improvement feasible to all outputs of a value stream. However, it is often desirable to have variable degrees of improvement across all the outputs of a value stream, in that it may be desirable at a particular time to improve, for example, profit margin by a larger proportion than say schedule stability. In such circumstances, more advanced DEA allows weights to be imposed on a particular output or group of outputs to make more restrictive comparative evaluation.

"take in Table 6"

6. Managerial implications

A key attribute of a robust performance measure system is its ability to provide information to enhance the organisation's strategic goal. The traditional performance measurement techniques offer a useful first step but they are not sufficiently future-oriented or externally focused. Furthermore, traditional techniques are not sufficiently robust in allowing management to identify the desired level of improvement. The DEA approach allows management to link performance with external factors, in this case, uncertainties in supply, process, demand and control. In doing so, it allows managers to address key questions important in making strategic as well as key tactical decisions. Questions such as: how does the performance of our supply chain compare with the performance of best performing supply chain actors with reference to the environmental uncertainties faced collectively by all supply chain actors?; and where do we need to improve our performance and by how much given the environmental uncertainties we face on the supply, processing, demand and control side? Clear answers to these questions allow managers to better align the supply chain they manage to the demands of the external environment by allocating scarce resources to where it is needed and instigating improvement projects.

The performance management techniques described in this paper enable managers of a DMU to compare their performance with the best performing DMUs or a selected reference DMU. This provides managers with a totally objective account of how well their DMU is performing relative to other DMUs as well as the most efficient DMUs. By applying this technique, managers can discriminate between the most efficient and less efficient DMUs (supply chains). It enables not only comparison of like with like, but allows managers to pinpoint weaknesses and set appropriate improvement targets. Moreover, managers can identify suitable role models (DMUs other than those on the efficient frontier) and systematically improve target levels. The flexibility to select an appropriate role model is of significant benefit.

Environmental uncertainties have a major impact on the performance of the supply chain and managerial decisions. The performance management technique discussed in this paper enables managers to establish how well their DMU is aligned with the uncertainties of the external environment vis-à-vis the best aligned DMU. The ability to align the organization with the demands of external environment is an important source of competitiveness.

The diagnostic model presented is applied in a cross-sectional manner and includes a group of independent DMUs. However, comparison between a group of DMUs belonging to a single organisation and temporal performance comparison are among key benchmarking approaches (Ghobadian *et al.*, 2001). Managers can therefore use the same ideas to develop internal cross-sectional comparison. This is particularly useful in the case of multinational companies operating many different DMUs. Alternatively the model could be used to identify periods where performance was optimal in the temporal study of a single supply chain value stream. That is, instead of comparing one value stream to another, the DEA evaluation can be conducted in a longitudinal manner to determine if a value stream is becoming more or less efficient over time given its environmental uncertainty conditions. This would enable the managers of the value stream to identify the periods when the value stream best demonstrates its capacity to deal with its environmental uncertainty characteristics. The supplementary managerial analysis could then be used to identify particular management or manufacturing practices that have underpinned this performance. The deployment of this DEA-based diagnostic tool to evaluate the overall performances of value streams for the purpose of performance improvement could equally be applied to other manufacturing sectors. To this end, the output side of the model can be modified according to various contextual manufacturing goals and considerations.

Despite the perceived advantages of DEA, a few caveats regarding its use generally and in this diagnostic reference application need to be made. It should be noted that DEA is only an evaluation technique. Whilst our application incorporates considerable information about each value stream's supply and demand environment, through the specifically selected DEA input variable *uncertainty*, it applies no judgement in reaching its evaluation. As such, the managers of the value streams under investigation should use DEA only as an indicator of any problems or inefficiencies, and further analysis should be undertaken prior to implementing DEA recommendations or taking action based on them (Easton *et al.*, 2002). It may be the case that the targets identified by the diagnostic evaluation are neither desirable nor achievable in reality (Easton *et al*., 2002). Additional managerial analysis should be undertaken to delineate the connections between the management and manufacturing practices of the value streams and the diagnostic results.

7. Conclusions and future research directions

The exploratory study presented in this paper demonstrates the value of DEA in enabling DMU managers to establish an externally linked and future-oriented performance measurement system that permits them not only to identify where the performance of their DMU lags behind that of best performing DMUs, but also allows them to establish realistic improvement targets. In this application the DMUs were supply chain value streams in the European automotive industry sector. The model used in this study shows how environmental uncertainty of the whole system (supply, processing, demand and control) can be contextualised and incorporated into a diagnostic reference model. This is of significant importance because it links performance with the external environment and both contingency and co-alignment theories suggest that environmental alignment is a key source of sustained competitive advantage.

DEA overcomes some of the key shortcomings of the traditional approaches to measuring performance within the supply chain, such as ratio analysis and financial measures. The traditional methods are not externally focused in that they do not seek to link performance with the operating environment. Furthermore, they predominately take an economic perspective, focusing on cost and time and ignoring other factors that influence the overall performance of the value stream such as institutional factors. Therefore, they are unable to fully reflect the efficiency/effectiveness of the value stream because they fail to completely reflect the multi-goal/dimensional nature of modern supply chains. They also do not readily lend themselves to construction of a single performance index taking into account continuous and categorical variables side by side. DEA overcomes these shortcomings and has enabled the construction of a diagnostic reference model that reflects the multi-goal, input and output character of modern supply chains.

A key contribution of the study presented in this paper is the development of a comparative performance evaluation model that measures and incorporates the influence of environmental uncertainty. Nevertheless, the authors are aware that uncertainty is one dimension of external environment and, as is pointed out later in this section, future research should consider inclusion of a more comprehensive dimension of environment. Furthermore, output measures might bear re-examination particularly if the industry context is different. The three output variables in our model were chosen to reflect the three essential dimensions of supply chain strategies identified by Beamon (1999), in the context of the European automobile industry. Although these output measures are generally useful in most manufacturing industry contexts, they may be considered to be context specific. In general, when using the CCR DEA model adopted here, there is a need for the number of decision-making units to be greater than the product of inputs and outputs in the model. This is a recognised and accepted limitation of DEA. Without a sufficient number of decision-making units, a large proportion of DMUs would be included on the efficient frontier and it would be difficult to determine which value streams in fact are the role models. The data sets used in this application have met this specification. Based on Dyson *et al.*'s (2001) guidelines, there would nevertheless be some scope in our model for extending the set of output measures without the requirement for extending the number of data points, if this were deemed appropriate to other industry contexts or in further research.

Arguably, the availability of data represents a potential hurdle to the full exploitation of this diagnostic reference model. Specifically, the focal business units have to make a commitment to collect the necessary data on a regular basis. However, it should be recognised that this situation is not specific to comparative performance evaluation using DEA. It equally applies to other non-mathematical benchmarking and reference model approaches. Repeated application periodically over time would facilitate continual evaluation and organisational learning and value stream process improvement.

In this study we relied on a composite measure of environment, that is to say, environmental uncertainty. We considered and developed a measure of environmental uncertainty for each element of supply chain and used these to create a system measure of uncertainty. However, environment has a number of other important dimensions (Misangyi *et al*., 2006), for example, munificence (the capacity to support organisations) and velocity (the rate of change). In future studies it is important to develop and include additional dimensions of the environment. Recent developments in the field of strategic management suggest that institutional polycentricity – formal and informal institutional forces – influence performance (Sirmon *et al.*, 2007). The formal institutional forces refer to regulations at national and local level, while the informal refer to culture and dominant beliefs. We suggest that future studies should include institutional dimensions. Finally, we looked at the performance of the whole system. In future research it would be useful to examine and compare the performance of constituent elements of supply chain to determine any difference between component and the whole system.

References

Akyuz, G.A. and Erkan, T.E., 2010. Supply chain performance measurement: a literature review. *International Journal of Production Research*, 48 (17), 5137–5155.

Anthanassopoulos, A.D., 1995. Performance improvement decision aid systems (PIDAS) in retailing organizations using data envelopment analysis. *Journal of Productivity Analysis*, 6 (2), 153–170.

Al-Faraj, T.N., Alidi, A.S. and Bu-Bshait, K.A., 1993. Evaluation of bank branches by means of data envelopment analysis. *International Journal of Operations and Production Management*, 13 (9), 45–52.

Astley, W.G. and Fombrun, C.J., 1983. Collective strategy: the social ecology of organizational environments. *Academy of Management Review*, 8 (4), 576–587.

Astley, W.G. and Van de Ven, A.H., 1983. Central perspectives and debates in organization theory. *Administrative Science Quarterly*, 28 (2), 245–273.

Azadeh, A., Ghaderi, S.F. and Ebrahimipour, V., 2007. An integrated PCA DEA framework for assessment and ranking of manufacturing systems based on equipment performance. *Engineering Computations: International Journal for Computer-Aided Engineering and Software*, 24 (40), 347–372.

Azadi, M. and Saen, R.F., 2011. Developing a WPF-CCR model for selecting suppliers in the presence of stochastic data. *OR Insight*, 24 (1), 31–48.

Beamon, B., 1999. Measuring supply chain performance. *International Journal of Operations and Production Management*, 19 (3–4), 275–292.

Beasley, J.E., 1995. Determining teaching and research efficiencies. *Journal of the Operational Research Society*, 46 (4), 441–452.

Biehl, M., Cook, W. and Johnston, D.A., 2006. The efficiency of joint decision making in buyer–supplier relationships. *Annals of Operational Research*, 145 (1), 15–34.

Borenstein, D., Luiz Becker, J. and Prado, V.J. do, 2004. Measuring the efficiency of Brazilian post office stores using data envelopment analysis. *International Journal of Operations and Production Management*, 24 (10), 1055–1078.

Bourgeois, L.J., 1984. Strategic management and determinism. *Academy of Management Review*, 9 (4), 586–597.

Bowersox, J.D. and Closs, D.J., 1996. *Logistical Management*, McGraw-Hill, Singapore.

Bowersox, J.D., Closs, D.J. and Stank, T.P., 1999. *21st Century Logistics: Making Supply Chain Integration a Reality*, Council of Logistics Management, Oak Brook, IL.

Braglia, M. and Petroni, A., 2000. A quality assurance-oriented methodology for handling trade-offs in supplier selection. *International Journal of Physical Distribution and Logistics Management*, 30 (2), 96–111.

Bytheway, A., 1995. Information in the supply chain: measuring supply chain performance. Working Paper SWP 1-95, Cranfield University, School of Management, Cranfield.

Carroll, G., 1993. A sociological view of why firms differ. *Strategic Management Journal*, 14 (4), 237–249.

Chandler, A.D., 1962. *Strategy and Structure: Chapters in the History of the American Industrial Enterprise*, MIT Press, Cambridge, MA.

Charnes, A., Cooper, W. and Rhodes, E., 1978. Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2, 429–444.

Charnes, A., Cooper, W.W. and Rhodes, E., 1981. Evaluating program and managerial efficiency: an application of data envelopment analysis to program follow through. *Management Science*, 27 (6), 668–697.

Charnes, A., Cooper, A., Levin, A. and Seiford, L., 1994. *Data Envelopment Analysis: Theory, Methodology and Applications*, Kluwer Academic Publishers, Norwell, MA.

Cherchye, L., Moesen, W., Rogge, N., Van Puyenbroeck, T., Saisana, M., Saltelli, A., Liska, R. and Tarantola, S., 2008. Creating composite indicators with DEA and robustness analysis: the case of the Technology Achievement Index. *Journal of the Operational Research Society*, 59, 239–251.

Chilingerian, J.A., 1994. Exploring why some physicians' hospital practices are more efficient: taking DEA inside the hospital, *In:* Charnes, A., Cooper, A., Levin, A. and Seiford, L. (Eds.), *Data Envelopment Analysis: Theory, Methodology and Applications*, Kluwer Academic Publishers, Norwell, MA, 167–193.

Childerhouse, P., 2002. *Enabling Seamless Market Orientated Supply Chains*, Ph.D. Thesis, Cardiff University.

Childerhouse, P., Disney, S.M. and Towill, D.R., 2000. The uncertainty circle as a value stream audit tool. *Proceedings of the 11th International Working Seminar on Production Economics*, Innsbruck, Austria, 21–25 February, 119–130.

Christopher, M., 2011. *Logistics and Supply Chain Management*, 4th Ed., FT Prentice Hall, London.

Davis, T., 1993. Effective supply chain management. *Sloan Management Review*, 34 (4), 35–46.

De Boer, L. and Telgen, J., 1998. Purchasing practice in Dutch municipalities. *International Journal of Purchasing and Materials Management*, 34 (2), 31–36.

Dotoli, M. and Falagario, M., 2012. A hierarchical model for optimal supplier selection in multiple sourcing contexts. *International Journal of Production Research*, 50 (11), 2953–2967.

Dyson, R.G., Allen, R., Camanho, A.S., Podinovski, V.V., Sarrico, C.S. and Shale, E.A., 2001. Pitfalls and protocols in DEA. *European Journal of Operational Research*, 132, 245–259.

Easton, L., Murphy, D.J. and Pearson, J.N., 2002. Purchasing performance evaluation: with data envelopment analysis. *European Journal of Purchasing and Supply Management*, 8 (3), 123–134.

Emery, F.E. and Trist, E.L., 1965. The casual texture of organizational environments. *Industrial Relations*, 18, 21–32.

Farrell, M., 1957. The measurement of productive efficiency. *Journal of the Royal Statistical Society*, A120, 253–281.

Saen, R. F., 2009. Supplier selection by the pair of nondiscretionary factors–imprecise data envelopment analysis models. *Journal of the Operational Research Society*, 60 (11), 1575–1582.

Forsund, F.R. and Hemaes, E., 1994. A comparative analysis of ferry transport in Norway, *In:* Charnes, A., Cooper, A., Levin, A. and Seiford, L. (Eds.), *Data Envelopment Analysis: Theory, Methodology and Applications*, Kluwer Academic Publishers, Norwell, MA, 285–311.

Ghobadian, A., Woo, H., Gallear, D., Viney, H. and Liu, J., 2001. *Benchmarking – Concept and Practice – With Particular Reference to the Finance Function*, CIMA Publishing, London.

Godsell, J., Diefenbach, T., Clemmow, C., Towill, D. and Christopher, M., 2011. Enabling supply chain segmentation through demand profiling. *International Journal of Physical Distribution and Logistics Management*, 41 (3), 296–314.

Grandori, A., 1984. A prescriptive contingency view of organizational decision making. *Administrative Science Quarterly*, 29 (2), 192–210.

Green, R.H. and Cooks, W.D., 2004. A free coordination hull approach to efficiency measurement. *Journal of the Operational Research Society*, 55, 1059–1063.

Gunasekaran, A., Patel, C. and McGaughey, R.E., 2004. A framework for supply chain performance measurement. *International Journal of Production Economics*, 87 (3), 333–347.

Harland, C., 1996. International comparisons of supply-chain relationships. *Logistics Information Management*, 9 (4), 35–38.

Hambrick, D.C., 1983. Some tests of the effectiveness and functional attributes of Miles and Snow's strategic types. *Academy of Management Journal*, 26 (1), 5–26.

Hewitt, F., 1994. Supply chain redesign. *International Journal of Logistics Management*, 5 (2), 1–9.

Hofer, C., 1975. Toward a contingency theory of business strategy. *Academy of Management Journal*, 18 (4), 784–810.

Jalalvand, F., Teimoury, E., Makui, A., Aryanezhad, M.B. and Jolai, F., 2011. A method to compare supply chains of an industry. *Supply Chain Management: An International Journal*, 16 (2), 82–97.

Jauch, L.R., Osborn, R.N. and Glueck, W.F., 1980. Short term financial success in large business organizations: the environment–strategy connection. *Strategic Management Journal*, 1 (1), 49–63.

Johnson, P., Klassen, R., Leenders, M. and Fearon, H., 2002. Determinants of purchasing team usage in the supply chain. *Journal of Operations Management*, 20 (1), 77–89.

Katz, D. and Kahn, R.L., 1966. *The Social Psychology of Organizations*, Wiley, New York.

Khandwalla, P.N., 1977. *The Design of Organizations*, Harcourt Brace Jovanovich, New York.

Knox Lovell, C., Walters, L.C. and Wood, L.L., 1994. Stratified models of education production using modified DEA and regression analysis, *In:* Charnes, A., Cooper, A., Levin,

A. and Seiford, L. (Eds.), *Data Envelopment Analysis: Theory, Methodology and Applications*, Kluwer Academic Publishers, Norwell, MA, 329–351.

Koutsoukis, N-S., Dominguez-Ballesteros, B., Lucas, C.A. and Mitra, G., 2000. A prototype decision support system for strategic planning under uncertainty. *International Journal of Physical Distribution and Logistics Management*, 30 (7/8), 640–660.

Kuo , R.J., Lee, L.Y. and Hu, T-L., 2010. Developing a supplier selection system through integrating fuzzy AHP and fuzzy DEA: a case study on an auto lighting system company in Taiwan. *Production Planning and Control*, 21 (5), 468–484.

Lawrence, P., 1981. The Harvard Organization and Environment Research Program, *In:* Van de Ven, A. and Joyce, W. (Eds.), *Perspectives of Organization Design and Behaviour*, Wiley & Sons, New York, 311–337.

Lee, J. and Miller, D., 1996. Strategy, environment and performance in two technological contexts: strategic contingency theory in a Korean setting. *Organization Studies*, 17 (5), 729–750.

Li, D. and O'Brien C., 1999. Integrated decision modeling of supply chain efficiency. *International Journal of Production Economics*, 59 (1–3), 147–157.

Li, D-C. and Dai, W-L., 2009. Determining the optimal collaborative benchmarks in a supply chain. *International Journal of Production Research*, 47 (16), 4457–4471.

Liang, Y-C. and Fang, N., 2011. Supplier productivity and quality performance evaluation in the TFT-LCD industry. *Asia-Pacific Journal of Operational Research*, 28 (6), 787–802.

Liang, L., Li, Z-Q., Cook, W.D. and Zhu, J., 2011. Data envelopment analysis efficiency in two-stage networks with feedback. *IIE Transactions*, 43 (5), 309–322.

Liu, J., Ding, F-Y. and Lall, V., 2000. Using data envelopment analysis to compare suppliers for supplier selection and performance improvement. *Supply Chain Management: An International Journal*, 5 (3), 143–150.

Lockamy, A., Childerhouse, P., Disney, S.M., Towill, D.R. and McCormack, K., 2008. The impact of process maturity and uncertainty on supply chain performance: an empirical study. *International Journal of Manufacturing Technology and Management*, 15 (1), 12–27.

Mahdiloo, M., Noorizadeh, A. and Saen, R.F., 2012. Suppliers ranking by cross-efficiency evaluation in the presence of volume discount offers. *International Journal of Services and Operations Management*, 11 (3), 237–254.

Mason-Jones, R. and Towill, D.R., 1998. Shrinking the supply chain uncertainty circle. *IOM Control*, 24 (7), 17–22.

Melnyk, S.A., Stewart, D.M. and Swink, M., 2004. Metrics and performance measurement in operations management: dealing with the metrics maze. *Journal of Operations Management*, 22 (3), 209–219.

Miles, R.E. and Snow, C.C., 1978. *Organizational Strategy, Structure and Process*, McGraw-Hill, New York.

Min, H. and Joo, S. J., 2006. Benchmarking the operational efficiency of third party logistics providers using data envelopment analysis. *Supply Chain Management: An International Journal*, 11 (3), 259–265.

Mintzberg, H., 1979. *Structuring of Organizations*, Prentice-Hall, Englewood Cliffs, NJ.

Misangyi, V.F., Elms, H., Greckhamer, T. and Lepine, J. A., 2006. A new perspective on a fundamental debate: a multilevel approach to industry, corporate, and business unit effects. *Strategic Management Journal*, 27 (6), 571–590.

Pasiouras, F., 2008. International evidence on the impact of regulations and supervision on banks' technical efficiency: an application of two-stage data envelopment analysis. *Review of Quantitative Finance and Accounting*, 30 (2), 187–223.

Pina, V. and Torres, L., 1992. Evaluating the efficiency of nonprofit organizations: an application of data envelopment analysis to the public health service. *Financial Accountability & Management*, 8 (3), 213–224.

Ray, S.C. and Kim, H.J., 1995. Cost efficiency in the US steel industry: a nonparametric analysis using data envelopment analysis. *European Journal of Operational Research*, 8 (3), 654–671.

Reiner, G. and Hofmann, P., 2006. Efficiency analysis of supply chain processes. *International Journal of Production Research*, 44 (23), 5065–5087.

Sabri, E.H. and Beamon, B.M., 2000. A multi-objective approach to simultaneous strategic and operational planning in supply chain design. *Omega*, 28 (5), 581–598.

Saranga, H. and Moser, R., 2010. Performance evaluation of purchasing and supply management using value chain DEA approach. *European Journal of Operational Research*, 207 (1), 197–205.

Saunders, M., Lewis, P. and Thornhill, A., 2002. *Research Methods for Business Students*, 3rd Ed., Financial Times Prentice Hall, Harlow.

Seiford, L.M., 1996. Data envelopment analysis: the evolution of the state of the art (1978–1995). *Journal of Productivity Analysis*, 7, 99–137.

Sevkli, M., Koh, S.C.L., Zaim, S., Demirbag, M. and Tatoglu, E., 2007. An application of data envelopment analytic hierarchy process for supplier selection: a case study of BEKO in Turkey. *International Journal of Production Research*, 45 (9), 1973–2003.

Sirmon, D.G., Hitt, M.A. and Ireland, R.D., 2007. Managing firm resources in dynamic environments to create value: looking inside the black box. *Academy of Management Review*, 32 (1), 273–292.

Slack, N., Chambers, S. and Johnston, R., 2004. *Operations Management*, 4th Ed., FT Prentice Hall, Harlow.

Storey, J., Emberson, C., Godsell, J. and Harrison, A., 2006. Supply chain management: theory, practice and future challenges. *International Journal of Operations & Production Management*, 26 (7), 754–774.

Strandholm, K., Kumar, K. and Subramanian, R., 2004. Examining the interrelationships among perceived environmental change, strategic response, managerial characteristics, and organizational performance. *Journal of Business Research*, 57 (1), 58–69.

Talluri, S. and Baker, R. C., 2002. A multi-phase mathematics programming approach for effective supply chain design. *European Journal of Operational Research*, 141 (3), 544–558.

Thanassoulis, E., Dyson, R. and Foster, M., 1987. Relative efficiency assessments using data envelopment analysis: an application to data on rates departments. *Journal of the Operational Research Society*, 38 (5), 397–411.

Thompson, J.D., 1967. *Organizations in Action*, McGraw-Hill, New York.

Towill, D., Childerhouse, P. and Disney, S., 1999. Speeding up the progress towards effective supply chain management. Occasional Paper No. 57, Department of Maritime Studies and International Transport, Cardiff University.

Towill, D., Childerhouse, P. and Disney, S., 2002. Integrating the automotive supply chain: where are we now? *International Journal of Physical Distribution & Logistics Management*, 32 (2), 79–95.

Van der Vorst, J.G.A.J. and Beulens, A.J.M., 2002. Identifying sources of uncertainty to generate supply chain redesign strategies. *International Journal of Physical Distribution & Logistics Management*, 32 (6), 409–430.

Vaz, C.B., Camanho, A.S. and Guimarães, R.C., 2010. The assessment of retailing efficiency using Network Data Envelopment Analysis. *Annals of Operations Research*, 173 (1), 5–24.

Weber, C., 1996. A data envelopment analysis approach to measuring vendor performance. *Supply Chain Management*, 1 (1), 28–39.

Wilding, R., 1998. The supply chain complexity triangle: uncertainty generation in the supply chain. *International Journal of Physical Distribution & Logistics Management*, 28 (8), 519–676.

Wu, D. and Olson, D. L., 2010. Enterprise risk management: a DEA VaR approach in vendor selection. *International Journal of Production Research*, 48 (16), 4919–4932.

Yang, F., Wu, D., Liang, L., Bi, G. and Wu, D.D., 2011. Supply chain DEA: production possibility set and performance evaluation model. *Annals of Operations Research*, 185 (1), 195–211.

Yasai-Ardekani, M. and Nystrom, P.C., 1996. Designs for environmental scanning systems. *Management Science*, 42 (2), 187–204.

Xu, J., Li, B. and Wu, D., 2009. Rough data envelopment analysis and its application to supply chain performance evaluation. *International Journal of Production Economics*, 122 (2), 628–638.

Appendix 1. The DEA model

(a) Rating the overall supply chain performance

Model M1 set up to assess the performance of observation j_0.

$$\text{Min } Z = U_{us} US_{j0}$$

subject to

$$\begin{aligned} & V_{pm} PM_{j0} + V_{dw} DW_{j0} + V_{ss} SS_{j0} = 100 \\ & V_{pm} PM_{j0} + V_{dw} DW_{j0} + V_{SS} SS_{j0} - U_{us} US_{j0} \leq 0 \qquad (M1) \\ & V_{pm}, V_{dw}, V_{ss}, U_{us} \geq 0.0001 \end{aligned}$$

where
US = uncertainty score
PM = profit margin
DW = delivery window
SS = schedule stability

N.B. In the formulation, the subscript j identifies each of the observed supply chains $(j = 1\ldots.j_{0\ldots}20)$. V_{pm}, V_{dw}, V_{ss}, U_{us} are weights attaching to PM, DW, SS and US respectively, and they are the variables in this model. The notation j_0 denotes a focal supply chain. Each supply chain becomes a focal one, in turn, when its efficiency score is computed. The relative performance of supply chain j_0 is $E_{j0} = 100/Z^*$, Z^* being the optimal value of Z in model M1. (For the derivation of the full DEA model see Charnes *et al*. (1994).) E_{j0} is the proportion supply chain j_0 achieves of the maximum output levels it could have achieved if it operated efficiently. Supply chain j_0 is relatively efficient if $E_{j0} = 1$.

(b) Peer references for under-performing supply chains

Efficient peers for supply chain j_0 are readily identified by the fact that if the jth supply chain is an efficient peer to supply chain j_0 then at the optimal solution to model M1 the constraint

$$V_{pm} PM_{j0} + V_{dw} DW_{j0} + V_{ss} SS_{j0} - U_{us} US_{j0} \leq 0 \qquad J = 1 \ldots..j_0\ldots.20 \text{ is binding.}$$

(c) Setting targets for improvement

$$\text{Max Z} = \Theta + 0.001\,(SUS + SDW + SPM + SSS)$$

subject to

$$\sum_{j}^{21} US_j \lambda_j + SUS = US_{j0}$$

$$\sum_{j}^{21} PM_j \lambda_j = SPM + \Theta PM_{j0}$$

$$\sum_{j}^{21} DW_j \lambda_j = SDW + \Theta DW_{j0} \qquad \text{(M2)}$$

$$\sum_{j}^{21} SS_j \lambda_j = SSS + \Theta SS_{j0}$$

$\lambda_j\, j$ = 1.....21, *SSS*, *SDW*, *SPM* and *SUS* ≥ 0, Θ is unconstrained.

In this model, λ_j, Θ, *SSS*, *SDW*, *SPM* and *SUS* are the variables. Notation is otherwise as in model M1. This model identifies feasible output levels which offer the maximum pro rata increase that is represented by the optimal value of the factor Θ to the current output levels of supply chain j_0 given its uncertainty levels. The optimal values of *SSS*, *SDW*, *SPM* and *SUS* identify any further input reductions or output increases that might have been feasible after the pro rata rises in the output levels. These input and output levels are *SS'*, *DW'*, *PM'* and *US'* for schedule stability, delivery window, profit margin and uncertainty score respectively, where:

$$SS' = \sum_{i}^{20} SS_j \lambda_j *$$

$$DW' = \sum_{j}^{20} DW_j \lambda_j *$$

$$PM' = \sum_{j}^{20} PM_j \lambda_j *$$

$$US' = \sum_{j}^{20} US_j \lambda_j *$$

The superscript * denotes the optimal values of λ_j in model M2. The level of *DW', PM', US'* and *SS*' would render supply chain j_0 relatively efficient, and they can be used as targets for the supply chain. (For the full derivation of model M2, see Charnes *et al.*, 1978.)

Appendix 2. Primary data used for assessing uncertainty during Quick Scan (QS) investigations

Uncertainty score	Typical primary data used during Quick Scan investigation
Supply side	MOPs placed on suppliers especially schedule adherence, invoices, call-offs, BOM, forecasts, receipts, supplier quality reports, MRP, lead times, stock reports
Demand side	Delivery frequency, echelons to end consumer, marketplace variability, stage of product life cycle, customer ordering procedures, forecast accuracy
Process side	Scrap reports, cycle times and variability of cycle times, production targets and output, downtime reports, stock consolidations, costed BOM, capacity planning, asset register
Control side	Time series of customer orders, supplier orders, demand forecasts, kanban logic, batching rules, MRP logic, call-offs, purchase orders, BGOM number of variants, delivery frequency, number of completing PDPs

Sources: Childerhouse et al. *(2000); Towill* et al. *(2002)*

Appendix 3. Overview of the value stream sample

Location	Product Description	Value stream ID	Major value-adding process(es)
England	Diesel engine component	1	Machining and assembly
England	Petrol engine component	2	Automated assembly
England	Automotive sensor	3	Automated assembly
England	Automotive engine system component	4	Machining and assembly
England	Diesel engine	5	Final assembly
England	Diesel engine component	6	Machining
England	Automotive component	7	Heat treatment
England	Automotive component	8	Heat treatment
Scotland	Automotive component	9	Machining
Scotland	Automotive component	10	Machining
England	Automotive engine component	11	Machining and assembly
England	Automotive engine component	12	Machining and assembly
Germany	Petrol engine component	13	Forging
Germany	Diesel engine component	14	Forging
England	Petrol engine component	15	Machining and assembly
England	Diesel engine component	16	Machining and assembly
Germany	Automotive braking component	17	Machining
Wales	Automotive braking component	18	Distribution warehousing
Wales	Automotive braking component	19	Machining and assembly
Wales	Automotive braking component	20	Machining and assembly

Table 1. DEA applications in supply chain management

Author(s)	Application area	Contribution of the study
Easton *et al.* (2002)	Comparison of purchasing performance of 18 companies in the US petroleum industry.	Demonstrates the perceived utility of DEA towards an enhanced performance evaluation system.
Talluri and Baker (2002)	Presentation of a proposed multi-phase mathematical programming approach for effective supply chain design.	Demonstrates the use of DEA in identifying the optimal number of suppliers, manufacturers and distributors for supply chain network design.
Biehl *et al*. (2006)	Comparison of the effectiveness of joint decision making within 87 pairs of buyer–supplier relationships.	Demonstrates the use of DEA to examine the impact of the contingent variables on efficiency in supply chain relationships.
Min and Joo (2006)	Comparison of operational performance of six major third party logistics (3PL) firms with four consecutive years of performance measures.	Demonstrates the utility of DEA for measuring the competitiveness of third party logistics services.
Reiner and Hofmann (2006)	Comparison of supply chain efficiency/company performance in 65 European and North American companies.	Demonstrates the use of DEA as an integrated benchmarking tool.
Li and Dai (2009)	Comparison of operational efficiency of 25 and 50 respectively suppliers to the Taiwanese PC/notebook industry.	Demonstrates the use of DEA and sensitivity analysis to measure supply chain collaborative performance.
Xu *et al.* (2009)	Comparison of the supply chain network operation efficiency of six furniture manufacture supply chains in southwest China.	Demonstrates the use of rough DEA by integrating classical DEA and rough set theory for performance evaluation.
Kuo *et al.* (2010)	Comparison of the operational capabilities of 10 suppliers to an auto lighting system OEM in Taiwan.	Demonstrates the use of the fuzzy AHP method and fuzzy DEA for assisting organisations to make the supplier selection decision.
Saranga and Moser (2010)	Comparison of 120 firms across the globe with >US$3 billion turnover.	Demonstrates the use of a two-stage value chain DEA method for purchasing and supply management performance evaluation.
Jalalvand *et al*. (2011)	Comparison of supply chain (SC) performance of seven SCs in the Iran broiler industry.	Demonstrates the use of DEA and PROMETHEE II, as tools to compare SCs at the process level, business stage level and whole SC level.
Liang *et al.* (2011)	Comparison of the supply chain performance of 50 Chinese universities.	Demonstrates the use of DEA to model efficiency in two-stage serial processes where feedback variables are present.

N.B. The applications of DEA in the specific related sub-field of supplier selection/rating, for example Saen (2009), which demonstrates non-discretionary factors–imprecise DEA models for supplier selection, are too numerous to include in this table. Recent examples can be found in Sevkli *et al.* (2007), Saen (2009), Wu and Olson (2010), Liang and Fang (2011), Dotoli and Falagario (2012) and Mahdiloo *et al*. (2012).

Table 2. The variables used in the current DEA model

Variable type	Dimension	Variable
Input	Uncertainty condition	*Uncertainty score* (Total score of uncertainty)
Output	Resources utilisation	*Profit margin* [= (price-variable cost)/price]
Output	Customer satisfaction	*Delivery window* [= percent of orders delivered on or before the due date]
Output	System flexibility	*Schedule stability* [= percent variation of monthly actual against monthly schedule]

Table 3. Questionnaire used to assess the process, supplier, demand and control uncertainty sources

	Rating by QS team			
Questions asked of each supply chain	Strongly agree	Weakly agree	Weakly disagree	Strongly disagree
The value added process(es) generates low system uncertainty	1	2	3	4
The supplier side generates low system uncertainty	1	2	3	4
The demand side generates low system uncertainty	1	2	3	4
The system controls do not generate uncertainty	1	2	3	4

Source: Towill et al. *(2002)*

Table 4. Value stream data and DEA performance ratings

Value stream	Uncertainty score	Profit margin	Delivery window	Schedule stability	DEA rating	Peer reference value streams
VS1	13	1	12	76	0.4513	4, 18
VS2	11	1	12	15	0.5013	4, 18
VS3	8	5	12	70	0.7290	4, 18
VS4	6	15	12	99	1.0000	-
VS5	11	5	12	50	0.5197	4, 18
VS6	10	5	12	1	0.5600	4, 18
VS7	13	5	12	90	0.4575	4, 18
VS8	9	5	12	90	0.6609	4, 18
VS9	9	8	12	95.5	0.6644	4, 18
VS10	8	8	12	95.5	0.7475	4, 18
VS11	11	1.5	12	50	0.5197	4, 18
VS12	12	4	12	86	0.4937	4, 18
VS13	1	1.5	12	89	0.5402	4, 18
VS14	10	1.5	12	89	0.5942	4, 18
VS15	14	5	12	95.5	0.4271	4, 18
VS16	12	5	12	95	0.4983	4, 18
VS17	11	5	24	25	1.0000	-
VS18	8	5	1	25	0.2500	4
VS19	15	5	2	35	0.1414	4
VS20	12	5	2	77	0.3914	4

Table 5. Comparison of VS6 performance with its efficient peers

Variables	VS4:	VS17:		VS6:	
	actual input/ outputs	actual input/ outputs	scaled actual input/ outputs (scale=0.5454)	actual input/ outputs	scaled actual input/ outputs (scale=0.6000)
Input:					
uncertainty score	6.0	11.0	6.0	10.0	6.0
Outputs:					
delivery window	12.0	24.0	13.09	12.0	7.2
schedule stability	99.0	25.0	13.63	1.0	0.6
profit margin	15.0	5.0	2.73	5.0	3.0

Table 6. Output targets for each DEA inefficient value stream

Value stream ID	Delivery window target	Delivery window achieved (percent)	Schedule stability target	Schedule stability achieved (percent)	Profit margin target	Profit margin achieved (percent)
VS1	26.59	45.13	168.4	45.13	25.87	3.87
VS2	23.94	50.13	29.92	50.13	5.71	17.51
VS3	16.64	72.12	96.02	72.90	14.18	35.26
(VS4)	(12)	(100)	(99)	(100)	(15)	(100)
VS5	23.09	51.97	96.21	51.97	15.24	32.81
VS6	21.43	56.00	53.21	1.88	8.93	55.99
VS7	26.23	45.75	196.71	45.75	29.94	16.70
VS8	18.16	66.08	136.18	66.09	20.73	24.12
VS9	18.06	66.45	143.73	66.44	21.81	36.68
VS10	16.50	72.73	127.76	74.75	19.39	41.26
VS11	23.09	51.97	96.21	51.97	15.24	9.84
VS12	24.30	49.38	174.18	49.37	26.58	15.05
VS13	22.21	54.03	164.75	54.02	25.09	5.98
VS14	20.19	59.44	149.78	59.42	22.81	6.58
VS15	28.09	42.72	223.59	42.71	33.93	14.74
VS16	24.08	49.83	191.65	49.83	29.09	17.19
(VS17)	(24)	(100)	(25)	(100)	(5)	(100)
VS18	16.00	6.25	132.00	18.94	20.00	25.00
VS19	30.00	6.67	247.50	14.14	37.50	13.33
VS20	24.00	8.33	198.00	39.14	30.00	16.67