

Testing the theory of performance frontiers in the era of Industry 4.0

Rui Sousa (rsousa@porto.ucp.pt)

Universidade Católica Portuguesa, Católica Porto Business School and CEGE

Behrouz Arabi

INESC TEC, Faculdade de Engenharia, Universidade do Porto

Ana Camanho

Faculdade de Engenharia, Universidade do Porto

Conceição Silva

Universidade Católica Portuguesa, Católica Porto Business School and CEGE

Giovani da Silveira

University of Calgary, Haskayne School of Business

Abstract

Although the Theory of Performance Frontiers (TPF) has been central to understand manufacturing strategy choices and performance, attempts to empirically test it have been few and incomplete. Over the last decade there has been significant development of new Advanced Manufacturing Technologies (AMTs), captured by labels such as industry 4.0, which may hold the potential to revolutionize established theory. This study employs Data Envelopment Analysis to examine whether the TPF holds in this new environment, considering operating frontiers and asset frontiers determined by recent AMTs. Based on data from 931 manufacturers, we provide insights for manufacturing strategy associated with recent AMTs.

Keywords: Manufacturing Strategy, Performance Frontiers, DEA.

Introduction

The Theory of Performance Frontiers (TPF) (Schmenner and Swink, 1998) is core to understand manufacturing strategy choices and performance. The theory is based on a number of tenets. First, performance includes multiple dimensions, typically quality, delivery, flexibility and cost. Rooted on the notions of Data Envelopment Analysis (DEA) (Charnes et al., 1978) a performance frontier is defined by the maximum composite performance that can be achieved by a manufacturing unit given a set of manufacturing strategy choices. Second, the theory distinguishes between choices that affect a manufacturing unit's physical assets and its operating policies. The former are associated with investments in technologies and give rise to an *asset frontier*. The latter are typically implemented by means of best practice programs (Rosenzweig and Easton, 2010), and give rise to an *operating frontier*. A plant's performance is immediately bounded by its

operating frontier and ultimately bounded by its asset frontier. The third tenet is related to the notions of *improvement* and *betterment*. Improvement is associated with removing inefficiencies from the transformation processes. It can take a plant closer to its operating frontier, but does not change this frontier. Betterment is associated with changing operating practices, thus resulting in moving the operating frontier. As a plant moves nearer its operating (or asset) frontier through improvement (or betterment), it becomes increasingly harder to simultaneously improve across multiple performance dimensions (law of cumulative capabilities) and improvements in one dimension may hurt other dimensions (law of trade-offs).

Despite the central role of the TPF in manufacturing strategy, attempts to empirically test it have been scarce and incomplete. In examining the predictions of TPF, few studies have employed frontier methods (e.g., DEA), and research has rarely considered operating and asset frontiers jointly (an exception is Lapre and Scudder, 2004). Thus, a first goal of our study is to conduct a more comprehensive test of the TPF, addressing some of the limitations of prior research.

Over the last decade there has been significant development of new Advanced Manufacturing Technologies (AMTs), captured by labels such as digitization of manufacturing and industry 4.0. Examples include additive manufacturing, robotics, autonomous systems, high precision technologies, smart factories, among others. Because of the different nature of these technologies, they may have the potential to transform operations management theory (Brennan et al., 2015; Holmström et al., 2016). Because of differences in adoption among plants, it is more likely to find plants operating with significantly different asset frontiers and with various distances between operating and asset frontiers. Thus, a second goal of our study is to test the TPF in this new context and to provide insights for manufacturing strategy associated with emerging AMTs. We address these goals by using DEA to analyse data from a large-scale international survey of 931 manufacturers from 22 countries.

A DEA approach to the theory of performance frontiers

One difficulty in the use of DEA to examine the TPF is that the theory works in terms of individual frontiers for each plant, which are not directly observable. DEA operates by identifying, within a group of units, those that are at the frontier (cannot improve in one dimension of performance without deteriorating another) and those that are below the frontier (can improve across all dimensions of performance). Because in DEA the notion of a frontier applies to a sample of units, rather than individual units, the empirically derived frontier may not coincide with the theoretical frontier of an individual plant (Rosenzweig and Easton, 2010).

We develop a method to make DEA amenable to empirically test the TPF, based on the identification of groups of plants with relatively homogeneous operating and asset frontiers. The asset frontier is operationalized by the degree of implementation of advanced manufacturing technologies and the operating frontier by the level of use of best practices (quality management, lean and new product development). Using cluster analysis, we create four groups of plants with homogeneous frontiers: G1 (High Assets, High Practices), G2 (High Assets, Low Practices), G3 (Low Assets, High Practices), G4 (Low Assets, Low Practices). We then employ DEA to estimate the operating frontier shared by the plants within each of the groups (and which is close to the unobserved theoretical frontiers of individual plants). This frontier is constructed using the performance dimensions of quality, delivery, flexibility and cost.

Research hypotheses

We develop hypotheses based on the TPF for different relative positions of the operating practice and asset frontiers, covering the main tenets of the theory. First, we consider betterment programs in the TPF. The theory posits that by investing in operating practices plants can simultaneously improve across multiple performance dimensions, thus pushing their operating frontier outward (Schmenner and Swink, 1998). The examination of this prediction requires the consideration of plants with similar asset frontiers (Schmenner and Swink, 1998; Sarmiento and Shukla, 2011). We put forward the following hypothesis:

H1. Among plants with similar asset frontiers, the operating frontier of those with high levels of operating practices ($G1/G3$) dominates the operating frontier of those with low levels of operating practices ($G2/G4$).

The level of investment in operating practices is expected to depend on the relative position of a plant's asset and operating frontiers (Cai and Yang, 2014; Rosenzweig and Easton, 2010). A firm with a lower asset frontier has less scope for improvement of its operating frontier (though betterment) than does one with a higher asset frontier. In contrast, a plant with a higher asset frontier has a stronger incentive to improve its operating frontier, to fulfil a larger share of the performance potential of its assets (Cai and Yang, 2014). We submit the following hypothesis:

H2. The level of use of operating practices is higher among plants with a high asset frontier ($G1+G2$) than among plants with a low asset frontier ($G3+G4$).

According to the TPF, as a plant moves nearer its asset frontier through betterment, it will experience increasing trade-offs across multiple performance dimensions (Schmenner and Swink, 1998; Lapre and Scudder, 2004). Thus, for plants with similar asset frontiers, we would expect that, as the operating frontier moves closer to the asset frontier, the contribution of additional betterment efforts to the simultaneous improvement of multiple performance dimensions over time decreases. We put forward the following hypothesis:

H3. Among plants with similar asset frontiers ($G1-G2/G3-G4$), the impact of additional betterment initiatives on the simultaneous improvement of multiple performance dimensions over time is higher for those with a low operating frontier ($G2/G4$) than for those with a high operating frontier ($G1/G3$).

Finally, we address improvement programs in the TPF. The TPF posits that, as a plant moves nearer its operating frontier through improvement, the law of trade-offs is increasingly applicable, as opposed to the law of cumulative capabilities. In order to examine this, we need to consider plants that have comparable operating and asset frontiers. We submit the following hypothesis:

H4. Within each group of plants with similar operating and asset frontiers ($G1-G4$), the law of cumulative capabilities is less prevalent for the plants situated on or near the operating frontier (efficient or top performing plants) than for those situated far from the operating frontier (inefficient plants).

Data and measures

The analysis used data from the sixth edition of the International Manufacturing Strategy Survey (IMSS-VI). The IMSS-VI was carried out in 2013-2014 in 22 countries. It targeted companies from ISIC 25-30, which included manufacturers of fabricated metal products, machinery, instruments, and equipment. Companies were identified mostly from national industry databases. Researchers initially contacted 7167 companies, of which 2586 agreed to participate. Valid responses were returned by 931 companies, representing 13% of the initial contacts and 36% of the questionnaires distributed. Answers were given at the business unit level by directors of manufacturing, operations, or related functions in the company.

The analysis included three sets of variables. *Advanced manufacturing technology* (AMT) was measured by the perceived level of implementation of advanced process technologies covered in the literature (e.g. Holmstrom et al., 2016), including advanced processes (e.g., 3D printing), “factory of the future” systems (e.g., digital factories) and process automation (e.g., robots).

Operations performance was operationalized by perceived results of the plant in quality (Q), cost (C), flexibility (F), and delivery (D) (Boyer and Lewis, 2002). Following the research model, we used two different time specifications, namely (i) *change* over the past three years (QC, CC, FC, DC) and (ii) *performance* at the time of data collection (QP, CP, FP, DP).

Operating practices was estimated by (i) the perceived *effort* over three years to implement (BPC), and (ii) the *present* level of implementation (BPP) of established manufacturing best practices including total quality management, lean, and product development (da Silveira and Sousa, 2010). Second-order best practices factors (*BPC*, *BPP*) were based on the respective first-order practice estimates.

The fieldwork questions, scales, and descriptive statistics are available upon request. All responses were given on five-point scales. All scales were successfully validated using confirmatory factor analysis (CFA), showing adequate validity, reliability and unidimensionality of measures.

Hypotheses testing

Clustering of plants

In order to test hypotheses, we grouped plants into four groups, each exhibiting similar operating and assets frontiers. First, we used cluster analysis to group plants according to their asset frontier (AMT variable), using the *k*-means algorithm in SPSS and the silhouette width measure to evaluate the cluster solutions (Rousseeuw, 1987). The best solution corresponded to two clusters (High Assets and Low Assets). There was no overlap in AMT values between the High Asset and the Low Asset groups. Second, we used the *k*-means clustering method to separate plants within each asset group into subgroups with a similar level of implementation of best practices (BPP). Both for the High Asset and Low Asset groups the best solution corresponded to two clusters. Table 1 describes the final four clusters. There is no overlap in BPP values between groups G1 and G2 nor between groups G3 and G4. Therefore, each group (G1-G4) has a good level of homogeneity in asset levels and best practices.

Table 1. Clusters according to the level of implementation of best practices.

Cluster	Sub-cluster	No. plants (%)	Mean AMT	Min-Max AMT	Mean BPP	Min-Max BPP	% of plants by size (*)
High Assets	G1. High Practices	209 (53%)	3.97	3.00-5.00	4.14	3.67-5.00	68% small 24% medium 8% large
	G2. Low Practices	187 (47%)	3.36	3.00-4.67	3.14	1.67-3.61	74% small 22% medium 4% large
Low Assets	G3. High Practices	172 (51%)	2.12	1.00-2.67	3.36	2.83-4.89	75% small 17% medium 8% large
	G4. Low Practices	168 (49%)	1.79	1.00-2.67	2.22	1.00-2.78	88% small 9% medium 3% large

(*) Large: >10,000 employees; Medium: 1,000-10,000 employees; Small: <1,000 employees.

Hypothesis H1

The operating frontiers for each of the four groups (G1-G4) are estimated using DEA (Charnes et al, 1978). The goal is to construct the frontier that envelops plants performance considering the four performance dimensions (QP, DP, FP and CP). We use DEA to build composite indicators. Under this logic, we have only outputs (performance indicators) to be aggregated, assuming that all plants are similar in terms of inputs (best practices and assets for each group, in our case). Thus, following Lovell et al. (1995), we can have a unitary input underlying the evaluation of every plant, interpreted as a “helmsman” attempting to steer the plant towards the maximization of outputs. By considering a unitary input level for all DMUs in the original DEA model of Charnes et al, (1978) and an input orientation, we obtain the model presented in (1). This linear programming model is known as “benefit of the doubt” (Cherchye et al., 2007).

$$\begin{aligned}
 \text{Max } E(y_{j_0}) &= \sum_{r=1}^s u_r y_{rj_0} & (1) \\
 \text{s.t. } \sum_{r=1}^s u_r y_{rj} &\leq 1, \quad j = 1, \dots, n \\
 u_r &\geq 0, \quad r = 1, \dots, s
 \end{aligned}$$

Model (1) is computed separately for each plant and the subscript j_0 refers to the plant whose relative efficiency is under evaluation. y_{rj} is the value of the performance dimension r ($r = 1, \dots, s$) observed for plant j . u_r is the weight given to performance dimension r to estimate its performance in the best possible light. The weights are the decision variables of the linear programming model. Model (1) involves finding values for u_r recurring to optimization. The performance (efficiency) measure for the plant j_0 is maximised (corresponding to a composite indicator of performance resulting from the aggregation of the four performance dimensions), subject to the constraint that the efficiency measures must be less than or equal to one for all plants in the sample when evaluated with similar weights. If using the optimal weights for plant j_0 no other plant reaches a score of aggregate performance higher than the value assigned to plant j_0 , it implies that the plant defines the operating frontier. In this case the objective function of (1) returns a score equal to one. Otherwise, plant j_0 is considered inefficient, meaning that it is located below the operating frontier.

Since we allow complete flexibility in the choice of the weights assigned to each performance dimension, a plant with a very good performance in one dimension may neglect its performance in the other dimensions. In practice, this means that a plant defining the operating frontier may have zero weights assigned to some performance dimensions. In these cases, the plants are not efficient in a Pareto sense, and have the potential to improve through the removal of slacks in the dimensions assigned a null weight without declining performance in the other dimensions. Note that an efficiency score below 1 signals potential for equiproportional (or radial) improvement in all performance dimensions, corresponding to the plants located below the frontier. We use the concept of radial efficiency (Farrell, 1957) to distinguish between efficient and non-efficient plants. In doing so, we consider that the plants located on the operating frontier have an efficiency score of 1 (which is not equivalent to Pareto-efficiency as seen above) and plants below the frontier have an efficiency score below 1.

Before testing H1, we analysed the extent to which the frontiers estimated for each group were robust (i.e. they are well populated and are not too distant from the bulk of firms in the analysis). This required checking for outliers that could be pushing the frontiers upwards. Nine plants were considered outliers and removed, resulting in a final sample used to test H1 composed of 207, 186, 171 and 163 plants in groups G1, G2, G3 and G4, respectively.

We run the linear programming model (1) to estimate the operating frontier of each of the four groups (G1-G4). To test H1, we need to compare the location of the operating frontiers of G1 and G2, as well as G3 and G4. To compare the location of frontiers from two different groups, we must additionally estimate a mixed-group efficiency score. This mixed-group efficiency score can be obtained using (2) (illustrating the comparison G1 vs G2). The superscript in the indicator ($y_{rj}^{G_2}$) represents the group to which the plant belongs to. The superscript in the efficiency score (E^{G_2}) corresponding to the objective function value indicates the group of plants used as comparators for the plant under assessment (j_0) in the linear programming model.

$$\begin{aligned}
 \text{Max } E^{G_2}(y_{j_0}^{G_1}) &= \sum_{r=1}^s u_r y_{rj_0}^{G_1} & (2) \\
 \text{s.t. } \sum_{r=1}^s u_r y_{rj}^{G_2} &\leq 1, \quad j = 1, \dots, n_{G_2} \\
 u_r &\geq 0, \quad r = 1, \dots, s
 \end{aligned}$$

In model (2), a score above 1 indicates that the plant under assessment, from group G1, has better performance than the plants in group G2, since in practice the plant is being assessed in relation to the frontier of G2. The ratio between the efficiency score of a plant j estimated via model (1) and (2) represents the radial distance between the frontiers of the two groups, as shown in (3).

$$\frac{E^{G_1}(y_j^{G_1})}{E^{G_2}(y_j^{G_1})} \quad (3)$$

A value of this ratio lower than 1 means that the efficiency score of the plant in G1 in relation to the G1 frontier is lower than the efficiency score of the plant in G1 in relation to the G2 frontier. In practice, this means that the frontier of G2 is below the frontier of G1 when the distance is estimated radially in the position where plant j_0 is located. If this ratio is estimated for all firms in the two groups and its value is always below 1, we can

conclude that there is empirical evidence that the high frontier does not crossover with the low frontier, signalling perfect domination of one frontier over another.

Following the approach developed by Camanho and Dyson (2006), the average distance between the frontiers of two groups can be estimated using a Malmquist-type index, as shown in (4). This index estimates the distance between the frontiers G1 and G2 considering the position of all plants in the two groups. A value of the index IF^{G1G2} lower than 1 means that the frontier of G2 is, on average, below the frontier of G1. The results of the index obtained for our sample are summarised in Table 2.

$$IF^{G1G2} = \left[\frac{\left(\prod_{j=1}^{n_{G1}} E^{G1}(y_j^{G1}) \right)^{1/n_{G1}} \left(\prod_{j=1}^{n_{G2}} E^{G1}(y_j^{G2}) \right)^{1/n_{G2}}}{\left(\prod_{j=1}^{n_{G1}} E^{G2}(y_j^{G1}) \right)^{1/n_{G1}} \left(\prod_{j=1}^{n_{G2}} E^{G2}(y_j^{G2}) \right)^{1/n_{G2}}} \right]^{1/2} \quad (4)$$

Table 2. Performance evaluation of plants considering the operating frontier estimated with DEA.

Index	Value	No. ratios < 1	No. ratios = 1	No. ratios > 1
IF^{G1G2}	0.9341	287	106	0
IF^{G3G4}	0.9338	310	24	0

The result of index IF^{G1G2} shows that the frontier of G2 is, on average, 6.59% below the frontier of G1 ($1-0.9341=0.0659$). Similarly, the result of index IF^{G3G4} shows that the frontier of G4 is, on average, 6.62% below the frontier of G3 ($1-0.9338=0.0662$). Consequently, hypothesis H1 is supported. Moreover, there is perfect dominance of G1/G3 over G2/G4, since all ratios are less than or equal to one. We repeated the analysis without removing the outliers, yielding similar results.

Hypothesis H2

The average of BPP for the High Asset plants (G1+G2; n= 396) is 3.67 and drops to 2.79 for the Low Asset plants (G3+G4; n=340). The difference between these two averages is statistically significant (t-test statistics = 17 and p-value = 0.000), supporting H2.

Hypothesis H3

In order to test H3, we require the examination of the impact of additional betterment initiatives on the simultaneous enhancement of multiple performance dimensions *over time*. This relates to the concept of enhancement trade-off (da Silveira, 2005). Following Lapre and Scudder (2004), we defined the variable Improvement Breadth (IB) as the number of performance dimensions that had improved in the last three years. We computed IB based on the performance change (last 3 years) variables (QC, CC, FC, DC). Each of these variables is composed of two items rated on a 1-5 scale, where 1 represents decline, 2 represents no change and 3, 4, and 5 represent different magnitudes of improvements. As such, we considered that a dimension improved if the corresponding change value (QC, CC, FC, DC) were higher than 2.00. Thus, IB is an ordinal variable that can take the values of 0, 1, 2, 3 and 4.

We then regressed IB (ordinal dependent variable) on BPC for each group (G1-G4), using cumulative logit regression. BPC had a positive impact on IB for all groups except G1, where this impact was not statistically significant. In addition, the impact - measured by the regression coefficients - was higher for groups with low operating practices

(G2/G4) when compared to the corresponding groups of high operating practices (G1/G3). This lends support to H3.

Hypothesis H4

In order to test H4, we require the examination of the extent to which the competitive position of a firm at a given point in time (relative performance across the four performance dimensions) requires trading-off performance across different dimensions. This corresponds to the concept of re-positioning trade-off (da Silveira, 2005). We estimate such trade-offs by looking at cross-sectional pairwise correlations across the four performance dimensions. We employ the pervasiveness of positive and negative correlations to infer about the extent to which such trade-offs occur.

We consider firms on or near the frontier based on the first quartile of efficiency scores given by the DEA analysis (H1). Since in all groups more than 25% of the firms have an efficiency score above 0.92, we considered 0.90 as the baseline threshold. Thus, we divided each group (G1-G4) into two sub-groups: plants on or near the frontier (efficiency score ≥ 0.90) and plants far from the frontier (efficiency score < 0.90).

Table 3 shows, for each group (G1-G4), the pairwise correlations across the four performance dimensions in each of the subgroups. All significant correlations in the ‘far from the frontier’ subgroups are positive, suggesting that the repositioning by the increase in one performance dimension may be accomplished with the simultaneous increase in other performance dimensions. For the ‘near the frontier’ subgroups, one or more significant correlations are negative, except in G3 (no significant correlations found). The number of positive correlations is much higher for the subgroups far from the frontier, than for those near the frontier. Taken together, the results lend support for H4. We repeated the analyses for several values of the efficiency threshold (0.85, 0.92, 0.95), yielding comparable results.

Table 3. Pairwise correlations across performance dimensions for plants near and far from the operating frontier.

Groups (no. of plants far/near the frontier)	Plants far from frontier (Efficiency < 90%)			Plants near frontier (Efficiency $\geq 90\%$)			Negative correlations in plants near/far from the frontier	Positive correlations in plants near/far from the frontier
	Cost	Del	Flex	Cost	Del	Flex		
G1(107/102)							1/0	1/6
Delivery	0.337**			-.035				
Flexibility	0.448**	0.423**		-.047	.069			
Quality	0.404**	0.442**	0.603**	-.247*	.008	.223*		
G2 (108/59)							2/0	1/4
Delivery	0.087			-.179				
Flexibility	0.073	0.331**		.113	-.103			
Quality	0.188*	0.329**	0.311**	-.332*	.258*	-.262*		
G3 (113/58)							0/0	0/3
Delivery	.104			-.128				
Flexibility	.139	.338**		-.102	-.066			
Quality	.057	.366**	.324**	-.069	.030	-.207		
G4 (120/48)							1/0	0/4
Delivery	.192*			-.179				
Flexibility	.099	.515**		-.514**	-.120			
Quality	-0.021	.448**	.401**	-.206	.177	-.271		

Significant correlations ($p < .05$) are in bold. * $p < .05$; ** $p < .01$

Conclusions

This study contributes to manufacturing strategy in two major areas. The first area is an increased understanding of the TPF and its empirical implications. Notably, we go beyond existing research by conducting a more comprehensive empirical test of the TPF by: i) covering a broad range of its core premises; ii) employing DEA to directly test the theory; iii) constructing composite performance indicators and frontiers based on a comprehensive set of performance dimensions (cost, quality, delivery, flexibility); iv) examining the interplay between operating and asset frontiers, namely in terms of its impact on trade-offs/cumulative capabilities. In doing so, we developed a novel empirical approach to examine the TPF based on DEA that can be employed by future studies.

Using this method, we offer a number of novel insights. Our findings (H1) show that the adoption of best practices such as quality management, lean and new product development pushes the operating frontier outwards. Because DEA optimizes the weights for the four performance dimensions for each plant, the operating frontiers that we have estimated include plans that, for example, have high performance on cost and low performance across the other dimensions (i.e., they excel on cost rather than differentiation) and vice-versa. Since our results show perfect domination of efficient high operating practice plants over efficient low operating practice plants, this provides evidence that plants can deploy (steer) best practice programs to support a range of effective competitive positions (e.g., based on low cost or differentiation). This is a novel finding that complements correlational empirical research that has shown positive impacts of best practices on firm performance (e.g., da Silveira and Sousa, 2010). We are not aware of other studies that have examined the impact of best practice programs on multiple performance dimensions through frontier methods.

Our use of DEA coupled with the analysis of data on operating practices and performance over time, also overcomes a number of limitations of past studies on trade-offs. As discussed earlier, by aggregating all units in correlational analyses - including units which are near and far from the frontier - past studies have failed to empirically detect trade-offs that occur as plants get nearer their operating or asset frontier (Sarmiento and Shukla, 2011). Our findings suggest that, although at a given point in time higher performing plants tend to display superior aggregate performance across multiple dimensions (H1), when they seek to further increase performance over time through betterment, they do seem to face increasing difficulty in improving across all performance dimensions simultaneously as they approach their asset frontiers (H3). Moreover, at a given point in time, plants situated on or near the operating frontier (efficient plants) seem to suffer from trade-offs across dimensions as they choose to reposition to different competitive locations along the frontier (relative performance across the four dimensions) (H4). In contrast, plants situated far from the frontier (inefficient plants) may, through improvement, achieve performance increase trajectories (which can involve change in competitive position) without trade-offs.

The second major area we contribute to is the understanding of the implications of emerging AMTs to manufacturing strategy. Overall, our findings show strong support for the TPF in this new technological environment. The findings (H2) suggest that such technologies significantly expand the use of best practice programs and, hence, the ability to push operating frontiers outwards, improving simultaneously across multiple performance dimensions. Moreover, by increasing the distance between asset and operating frontiers through the adoption of AMTs, plants are able to extend the range along which best practice programs generate strong returns and allow for the simultaneous improvement of multiple performance dimensions. Therefore, the adoption of AMTs such as advanced processes (e.g., 3D printing), digital factories and advanced

process automation (e.g., robots) can be a source of competitive advantage, regardless of competitive strategy (e.g., low cost vs differentiation).

Acknowledgments

Financial Support through Project “TEC4Growth” is gratefully acknowledged. Project “TEC4Growth – Pervasive Intelligence, Enhancers and Proofs of Concept with Industrial Impact/NORTE-01-0145-FEDER-000020” is financed by the North Portugal Regional Operational Program (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, and through the European Regional Development Fund (ERDF). Financial support from Fundação para a Ciência e Tecnologia (through project UID/GES/00731/2016) is gratefully acknowledged. Giovanni da Silveira’s research is supported by the Warren Dyer Fellowship in Advanced Supply Chain Management and Logistics at the Haskayne School of Business.

References

- Boyer, K., Lewis, M. (2002), “Competitive priorities: Investigating the need for trade-offs in operations strategy”, *Production and Operations Management*, Vol. 11 No. 1, pp. 9–20.
- Brennan, L., Ferdows, K., Godsell, J., Golini, R., Keegan, R., Kinkel, S., Srai S.J., Taylor, M. (2015), “Manufacturing in the world: where next?”, *International Journal of Operations & Production Management*, Vol. 35 No. 9, pp. 1253-1274.
- Cai, S., Yang, Z. (2014), “On the relationship between business environment and competitive priorities: The role of performance frontiers”, *International Journal of Production Economics*, Vol. 151, 131-145.
- Camanho, A., Dyson, R. (2006), “Data envelopment analysis and Malmquist indices for measuring group performance”, *Journal of Productivity Analysis*, Vol 26 No. 1, pp. 35-49.
- Charnes, A., Cooper, W., Rhodes, E. (1978), “Measuring the efficiency of decision making units”, *European Journal of Operational Research*, Vol. 2 No. 6, pp. 429-444.
- Cherchye, L., Moesen, W., Rogge, N., Van Puyenbroeck, T. (2007), “An introduction to benefit of the doubt composite indicators”, *Social Indicators Research*, Vol. 82 No. 1, pp. 111-145.
- da Silveira, G. J. (2005), “Improving trade-offs in manufacturing: Method and illustration”, *International Journal of Production Economics*, Vol. 95 No. 1, pp. 27-38.
- da Silveira, G. J., Sousa, R. (2010), “Paradigms of choice in manufacturing strategy: Exploring performance relationships of fit, best practices, and capability-based approaches”, *International Journal of Operations & Production Management*, Vol. 30 No. 12, pp. 1219-1245.
- Farrell M. (1957), “The measurement of productive efficiency”, *Journal of the Royal Statistical Society, Serie A*, pp. 252-67.
- Holmström, J., Holweg, M., Lawson B., Pil F., Wagner S. (2016), “The digitization of manufacturing”, *Call for Papers, Journal of Operations Management*.
- Lapre, M., Scudder, G. (2004), “Performance improvement paths in the U.S. airline industry: Linking trade-offs to asset frontiers”, *Production and Operations Management*, Vol. 13 No. 2, pp. 123–134.
- Lovell, C., Pastor, J., Turner, J. (1995), “Measuring macroeconomic performance in the OECD: A comparison of european and noneuropean countries”, *European Journal of Operational Research*, Vol. 87 No. 3, pp. 507-518.
- Rosenzweig, E., Roth, A. (2004), “Towards a theory of competitive progression: Evidence in high-tech manufacturing”, *Production and Operations Management*, Vol. 13 No. 4, pp. 354–368.
- Rousseuw, P. (1987), “Silhouettes: a graphical aid to the interpretation and validation of cluster analysis”, *Journal of Computational and Applied Mathematics*, Vol. 20, pp. 53-65.
- Sarmiento, R., Shukla, V. (2011), “Zero-sum and frontier trade-offs: an investigation on compromises and compatibilities amongst manufacturing capabilities”, *International Journal of Production Research*, Vol. 49 No. 7, pp. 2001-2017.
- Schmenner, R., Swink, M. (1998), “On theory in operations management”, *Journal of Operations Management*, Vol. 17 No. 1, pp. 97-113.