

A New Approach for Nonparametric Network Efficiency Analysis with Application to Daily Newspapers

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Abstract

Many organizations (DMUs) are comprised of networked sub-DMUs or departments, i.e., the outputs of some departments serve as inputs to others and vice versa. For example, in media-platform firms like newspaper companies, the outputs of the editorial department are inputs to the advertising department and vice versa. Extant approaches for efficiency analysis either ignore the network effects or make parametric assumptions to enable statistical inference on the estimated efficiencies. Hence, we develop a new method that incorporates the network effects and furnishes nonparametric inference on efficiencies. Applying the proposed method to the US daily newspaper industry, we not only demonstrate that it outperforms existing approaches, but also that it yields new insights into department-level efficiencies.

Keywords: Efficiency Analysis, Sliced Inverse Regression, Media-Platforms, Networked DMUs

Introduction

Efficiency benchmarking is a managerial tool used to compare several similar decision making units (DMUs) to identify top performing DMU(s) and compare their productivity against other DMUs (Charnes, Cooper & Rhodes 1978). The best-performing DMU is usually defined as one that is the most efficient, i.e. produces the most output(s) given available input(s).

A Bain & Company Management Tools Survey of senior executives of over 700 companies in 2003 found over 80% of firms used benchmarking. Benchmarking has become a primary instrument in firms' process and capability improvement efforts in various domains including marketing (Vorheis and Morgan 2007). Examples include the benchmarking of marketing divisions of high-technology firms (Dutta, Narasimhan and Rajiv 1999), salesperson performance (Parsons, 2004), advertising departments (Luo and Donthu 2005) and retail outlets (Gauri, Pauler, and Trivedi 2008).

This paper focuses on the issue of efficiency analysis of DMUs that are comprised of networked departments such as those in the media industry (e.g. newspapers, magazines, television and radio stations). There are several reasons for our special interest in media-platforms: First, the media industry is characterized by the presence of a few large companies that have each acquired several hundred independently operating DMUs (Picard, 2002). For example, the leading media giant Gannett Incorporated currently owns 82 daily newspapers and more than 200 weekly newspapers that each function as independent DMUs¹. Efficiency benchmarking could serve as a way to provide alert, timely, and accurate guidance to DMUs performing below the mark. Second, among media-industries, the daily newspaper industry sorely needs guidance on efficient allocation of resources as it faces troubling economic times

¹ Sourced from the company website [http://www.gannett.com/about/company_profile.htm]

due to dwindling circulations & advertising revenues (e.g., Bughin and Poppe 2005) . After several interviews with newspaper owners, publishers, and managers of syndicated data collection agencies, we find that no formal benchmarking analysis is performed to benefit the industry at large. There is also no academic application of benchmarking related to gauging the efficiency of media firms.

Additionally, the media-firm's business model makes the newspaper benchmarking problem novel albeit methodologically challenging. Specifically, many media firms are *two-sided* platforms, i.e. their key feature is that they bring together two groups of customers (users of content, buyers of advertising) and have to keep both of them on board to succeed (Rochet and Tirole, 2005, Sridhar, Mantrala, Naik, Thorson 2011).. This means there are at least three challenges that an appropriate firm-level efficiency analysis approach must overcome:

1. *It should produce efficiency scores at the department-level:* Since the tasks performed in acquiring and retaining their different customer groups are different, media-platforms are usually divided into departments, e.g., circulation and ad sales force departments, (Warner and Buchman 1991, pg. 13-15). Departments vary in terms of their efficiency in building and maintaining their designated end-user groups. Assessing their respective efficiencies in a media-platform is important because of their repercussions on each other.
2. *It should recognize that some departments' outputs are mutually inter-linked:* Some department outputs in a media-platform are inherently networked, i.e. the output that a department produces serves as input for the other. For example, the output of the media sales force department is sales of ad-space, ad-spots or banners on websites. This is greatly facilitated by the output that the content department creates, e.g. news content. In fact, a media salesperson usually carries recent figures pertaining to the output of the content department (e.g. number of stories about a certain topic, size of subscription base) to inform advertisers about the potential benefits of purchasing ad-space in this medium (Warner and Buchman, 1992). At the same time, the amount of advertising sold (output

of the sales department) is an input for the content department (Hamilton, 2004)². Any benchmarking analysis of media-firms must take this key feature into account.

3. *It should be capable of statistical inference about the impact of efficiency:* Numerous random factors (e.g. luck, weather) could influence the impact of the conversion of each media-firm department's inputs into outputs. Therefore, a stochastic media-benchmarking model that captures the role of random error in the conversion of inputs into outputs is needed (Luo and Donthu 2004). This allows us to estimate (rather than simply calculate) and statistically test (rather than assume) the impact of increase in departmental efficiency on the overall firm's outputs (e.g. Arnold et al 1996).

Currently, there is no available method that handles all the three challenges noted above. This paper's objective is to develop and demonstrate a suitable approach to benchmark media-platforms that addresses all three challenges. Specifically, we propose an approach that combines the relatively new techniques of *Network DEA* (NDEA) and *Multivariate Sliced Inverse Regression* (MSIR) to address all three challenges. Our proposed approach is fairly general and can also be used in benchmarking other (non-media) two-sided platforms (e.g. shopping malls). We demonstrate the approach by applying it to U.S. print newspaper firms. Using syndicated source data, we obtain the efficiencies of the newsroom, distribution and sales force department in each newspaper and also statistically assess the impact of increasing efficiency on the output-producing capability and financial performance of newspapers. This application shows how the proposed approach outperforms current approaches applied to platform-firms and offers substantive guidance to the newspaper industry.

The organization of this paper is as follows. We first review available procedures for benchmarking and their limitations with respect to the platform-firm benchmarking context. We

² As Hamilton (2004) notes “when news sell ‘eyeballs’ to advertisers, the question becomes what (advertising) content can attract readers or viewers rather than what value will consumers place on content”.

then describe our proposed approach and highlight its advantages. Next we describe the organization of print newspapers and the data we have regarding their inputs and outputs. Subsequently, we apply our approach to these data and compare the results with those of extant approaches in dealing with the benchmarking problem. To obtain managerial insights, we shed light on some key differences of high vs. low performing newspapers. We conclude with a discussion of the implications of our research for the newspaper industry, media-platforms, and the benchmarking literature.

Development of an Appropriate Benchmarking Procedure

Table 1 summarizes several commonly used approaches for benchmarking, highlighting their limitations with respect to benchmarking media-platforms.

Data Envelopment Analysis (DEA)

DEA is a popular and well-known benchmarking tool that calculates the efficiency of a DMU as a ratio of the outputs it produces to the inputs it consumes. When DMUs use multiple inputs to produce multiple outputs, a weighted ratio of outputs to inputs is preferred so that a scalar efficiency metric can be obtained. DEA is designed to calculate the weighting scheme for a DMU while at the same time, calculating its efficiency (Charnes, Cooper, and Rhodes, 1978). Specifically, DEA sets up a linear program to optimally determine the weights that enable each DMU to maximize its weighted ratio of outputs to inputs (efficiency) subject to all comparison DMUs' efficiencies using the same weights being less than or equal to one (Charnes, Cooper, and Rhodes, 1978). Thus, the weights for each DMU are chosen “to make it look the best in comparison with other units” (Dutta, Kamakura and Ratchford, 2004). Details pertaining to the calculation of the efficiency using DEA score are provided in Appendix A. A DMU is 100% efficient if the weighted ratio score is 1.

Because DEA is a non-parametric technique that requires no functional form assumptions about the production function, and can handle multiple outputs and multiple inputs with ease, applications of DEA in marketing (e.g. Horsky and Nelson 1996; Luo et al 2006) and other fields like banking are numerous (see Emrouznejad and Thanassoulis 2001 for an exhaustive list).

Column 2 in Table 1 evaluates the use of DEA as a tool for our application, i.e. media-platforms. To apply DEA to the media-platform setting, one could simply combine the outputs and inputs of the DMU regardless of which department they belong to and then obtain the DMU's efficiency score. However, this would provide scores like a "black-box" (Fare and Grosskopf, 2000), and the underlying idiosyncratic structure of the media-platform would not be modeled. Conversely, one could perform as many DEA analyses as there are departments by treating each department of a media-platform as a DMU that uses inputs to produce outputs. While this would overcome the challenge of providing departmental-level scores, it would ignore the two-sided feature of the media-platform, i.e. the relatedness of outputs. In general, outputs and inputs are not allowed to be interrelated in DEA and the technique is purely deterministic and cannot provide statistical inference about the impact of efficiency (Donthu and Yoo 1998). Therefore, it is not a comprehensive tool for our purpose (see Table 1).

Network DEA (NDEA)

Network DEA falls in the class of (*standard*) DEA models in that it also uses the mathematical programming idea to calculate the weights and efficiency of a DMU. The basic innovation of NDEA, first developed by Fare and Grosskopf (2000), is that it breaks a DMU into a set of smaller inter-connected sub-DMUs (departments) and calculates the overall efficiency score of a DMU as well as each sub-DMU's efficiency score. While doing so, it also recognizes that sub-DMUs may be structured so that one DMU's output may serve as another's input. It

does so by allowing two factors to influence the output that a particular sub-DMU (e.g. sales force of a media-platform) is responsible for: a) the inputs (e.g., salesmen) to the same department and the relevant outputs from another department (e.g., newsroom).

NDEA requires the specification of the networked input-output structure within a DMU. The details pertaining to the calculation of the efficiency scores through NDEA are provided in Appendix B. The outcome of an NDEA is the scalar efficiency score of each sub-DMU and the overall scalar efficiency score of the entire DMU.

NDEA continues to retain the non-parametric and multi-output advantages of DEA. NDEA's relatively recent development means that only a handful of empirical applications exist in the literature. For example, Lewis and Sexton (2004) apply NDEA to benchmark the recruiting and production departments (sub-DMUs) as well as the baseball franchises (DMU) within which they operate. The recruiting department uses salaries as inputs to produce player position-talent. The production department uses salaries as well as the player talents acquired (outputs from recruiting department) to produce wins. NDEA is useful in recognizing the role of the linked-quantity (player-talents) in the calculation of efficiency. Other NDEA applications exist in banking (Avkiran 2009) and transportation (e.g. Yu and Lin 2008).

Column 3 in Table 1 evaluates the use of NDEA as a tool for benchmarking media-platforms. To apply NDEA to benchmark media-platforms, we would identify the inputs, outputs and the linkages between one department and the other. In the media-platform setting, the content department's outputs serve as additional inputs to the advertising department and *vice versa*. The simultaneity in output-relatedness makes even the application of NDEA to the media-platform different from other applications such as Lewis and Sexton (2004) where simultaneity is not prevalent. By obtaining sub-DMU and DMU scores (Challenge 1) while accounting for

relatedness (Challenge 2), NDEA addresses the first two issues in Table 1. However, since NDEA is also purely deterministic, it cannot provide statistical inference about the impact of increasing a particular sub-DMU's efficiency on the outputs produced by the platform. Therefore, NDEA falls short of the comprehensiveness demanded by our problem.

Stochastic Frontier Analysis (SFA)

The advancement of SFA as a popular benchmarking technique is mainly due to the fact that it explicitly accounts for the role of random error in the calculation of efficiency (e.g. Aigner et al. 1977). A DMU is viewed as one that produces an output y^k while using a production technology given by $f(x^k, \beta)$ where x^k represents the inputs used by the firm, β represents the slope coefficient of x^k . SFA challenges the fundamental assumption that producers indeed produce as much as their technology would suggest. Specifically, it posits that while DMUs may try to produce outputs according to their technology they actually fall short by an amount v^k due to inefficiency. Efficiency in the SFA context is defined as the ratio of observed output produced by a firm to the maximum feasible output the DMU could have produced. Additionally, error (u^k) is incorporated in our knowledge of a firm's production function as well to account for the myriad influences of luck, chance etc. In sum, a firm's output is represented as

$$y^k = f(x^k, \beta) \cdot \exp(\varepsilon^k) \tag{1}$$

where ε^k represents the composite error terms consisting of the sum of a normal error term (u^k) and a one-sided error term ($v^k > 0$) which captures the inefficiency of a firm. Thus,

$$y^k = f(x^k, \beta) \cdot \exp(u^k - v^k) \tag{2}$$

In practice, the estimates and associated inference with respect to β , the variance of ε and the DMU specific estimates of inefficiency (v^k) can be obtained through maximum likelihood estimation after assuming suitable functional forms for $f(\cdot)$. Since it can provide a statistical test

as to whether a firm is 100% efficient (i.e. $v^k=0$), SFA has seen several applications in marketing (e.g. Kamakura et al. 1996; Dutta et al 1999, Luo and Donthu 2004).

Column 4 in Table 1 evaluates the use of SFA as a tool for benchmarking media-platforms. Similar to DEA, one could perform as many SFA analyses as there are departments by treating each department of a media-platform as a DMU that obtains inputs to produce outputs. This would enable us to obtain departmental-efficiency scores but again ignores the relatedness of outputs and thereby does not address the second challenge in question. SFA can provide us with strict hypotheses tests as to whether a firm is 100% efficient (Kumbhakar and Lovell 2000). Specifically, if a DMU is 100%, SFA says that this firm can indeed produce outputs according to its production function. Therefore, $v^k=0$ for that DMU. A strict hypothesis test that $E(v^k)=0$ has been suggested for this purpose (Battese and Coelli 1998). Therefore, SFA can indeed provide inference about the impact of efficiency on outputs. However, SFA usually assumes a Cobb-Douglas specification for $f(\cdot)$, which could be limiting in some contexts.

Two-Stage (DEA+ Ordinary Least Squares) Procedure

Arnold et al (1996) introduce a two-stage approach to perform benchmarking that retains the non-parametric advantages of standard DEA and the statistical-inference capabilities of regression analysis. They propose the joint use of DEA and Ordinary Least Squares (OLS), i.e. the results from a DEA analysis are incorporated into a statistical regression of outputs on inputs.

Specifically, for a set of n DMUs, a standard DEA is performed (Stage 1) to obtain the efficiency score of each DMU. The second stage consists of *two parts* in the case of a DMU producing multiple outputs. In the first part, the multiple outputs are condensed into one

composite output using a canonical correlation of outputs on inputs (Part 1). Specifically, if a DMU k produces s outputs denoted by y_s^k , then the composite output CY^k is defined as

$$CY^k = \sum_{j=1}^s \alpha_j \ln y_j^k \quad (3)$$

where α_j represents the canonical coefficients obtained by conducting a canonical correlation between the outputs and inputs. In the second part, the composite output CY^k is regressed on each of the inputs and the efficiency score of the DMU. If the DMU k used an input vector \mathbf{X}^k and an efficiency score ρ^k , the approach employs and estimates a Cobb-Douglas function

$$\ln CY^k = \beta_0 + \boldsymbol{\beta} \ln \mathbf{X}^k + \beta_e \rho^k + \varepsilon^k \quad (4)$$

where the coefficient β_e is the effect of efficiency (ρ^k) on the firm's composite output CY^k .

The advantage of the two-stage approach is that the efficiency scores ρ^k are obtained from a simple and non-parametric approach (DEA) and the inference about ρ^k can also be carried out through simple regression techniques (e.g. OLS). In a simulation study, Bardhan et al (1998) showed that the above two-stage method performs better than each of the approaches taken individually.

Column 5 in Table 1 evaluates the use of the two-stage (DEA + OLS) technique as a tool for benchmarking media-platforms. The first step involves a DEA similar to the one described earlier. As illustrated earlier, the DEA cannot take into account the relatedness among the various platform outputs while calculating the efficiency score. Therefore, the Arnold et al (1996) method cannot address the first two challenges in the media-platform context. However, it can be used to provide inference through the second stage by the use of canonical correlations

to condense the many media-platform outputs (Stage 2, Part 1) and then perform a regression of this condensed media-platform output on the inputs and the DEA efficiency score using a Cobb-Douglas function (Stage 2, Part 2). However, both parts involve limiting assumptions. The use of canonical correlations in Part 1 has several theoretical limitations including the assumption of a linear relationship between the dependent and independent variables (Tabachnik and Fidell, 2007, p. 569). Similarly, the Cobb-Douglas functional form assumes a multiplicative functional form relationship. While this seems quite plausible, this is a less flexible approach, and assumes the functional form is known *ab initio* and reduces some of the non-parametric advantages that the DEA step provides in the first place. In summary, the two-stage Arnold et al. (1996) approach also fails to meet the three criteria with which we evaluate it as a benchmarking tool for the media-platform context.

A New Two-Stage (NDEA + MSIR) Procedure

A critical review of each of the above techniques shows that no single method handles all the three challenges noted above. In this section, we combine the strengths of these techniques with the use of a novel dimension reduction technique introduced in the statistics literature (Multivariate Sliced Inverse Regression) to address all three challenges.

Specifically, like Arnold et al (1996), i.e. we use a 2-stage approach that combines the usefulness of DEA-based techniques and statistical techniques. However, we augment both stages of the Arnold et al (1996) procedure. Specifically, we use NDEA instead of DEA in Stage 1; and MSIR instead of canonical correlation and the Cobb-Douglas form in Stage 2. The second stage of the two-stage approach is to a) condense the multiple outputs of the firm into a composite output (Part 1) and b) perform a regression of the composite outputs on inputs and efficiency (Part 2). To alleviate the limitations in Part 1 and Part 2 of the Arnold et al. (1996)

approach, we propose the use of Sliced Inverse Regression (SIR) in Stage 2. Sliced inverse regression (or SIR) originated as a dimension reduction technique in data-rich environments (Duan and Li 1991). The basic representation of an SIR model is

$$y = g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \quad (5)$$

where y is a univariate vector of n observations ($n \times 1$), $g(\cdot)$ is an unknown function, X is a p dimensional matrix of n observations ($n \times p$), α is a $(k \times p)$ matrix vector of coefficients ($k < p$) and ε is the error term about which no distributional assumption is made. The combination of the k alpha vectors is known as the *effective dimension reduction* (EDR) space and helps us better understand the relationship between y and the entire vector X by condensing it into a smaller sub-space. SIR can be extended to a situation where there are many dependent variables (i.e. Y is a matrix) through the use of multivariate SIR (MSIR). Thus, similar to the k -dimensional EDR space of X ($k < p$), an l -dimensional sub-space of Y (called the most-predictable Y space or MP space Y) is found ($l < q$). The MSIR model is represented as

$$\begin{aligned} \theta_1' Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \\ \theta_2' Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \\ &\dots \\ \theta_l' Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \end{aligned} \quad (6)$$

The Technical Appendix (C) delineates how the EDR space α and the MPY space θ can be obtained through univariate SIR and MSIR respectively. When $k=1$ and $l=1$, we can use only 1 MPY space and 1 EDR space to condense the multiple outputs and multiple inputs respectively. We denote them as the composite X vector (COMP_X) and the composite Y vector (COMP_Y) for ease of exposition. MSIR generalizes Stage 2 of the Arnold et al (1996) approach as follows:

First, we note that that the COMP_X and COMP_Y terms can be obtained without any knowledge about the functional form of $g(\cdot)$ (Li, 1991). This flexibility of SIR-based techniques makes it outperform a plethora of techniques such as principal components analysis, partial least squares etc³. The canonical correlation approach used by Arnold et al (1996) in Part 1 of Stage 2 is also a special case of the MSIR approach, i.e. one that assumes that $g(\cdot)$ is a linear function.

Once the composite terms COMP_X and COMP_Y are obtained through non-parametric techniques, we can simply graph a scatter-plot to assess their relationship. (e.g. Gannoun, Girard, Guinot and Saracco 2004). We can then choose any appropriate functional form (including Cobb-Douglas) to capture the relationship between COMP_X and COMP_Y, which can subsequently be estimated. This means that the Cobb-Douglas approach used by Arnold et al (1996) in Part 2 of Stage 2 is also a special case of the MSIR approach.

To summarize, to perform benchmarking analysis of media-platforms, our approach involves the stages described in the following paragraph.

Stage 1: Identify the sub-DMUs, inputs, outputs and linked inputs of each sub-DMU of the media-platform. Perform an NDEA analysis to obtain the efficiency score of each sub-DMU.

Stage 2, Part 1: Perform an MSIR estimation where the Y matrix includes all the outputs produced by the media-platform and the X matrix includes all the inputs used by the media-platform and the efficiency terms of each sub-DMU. Obtain the COMP_Y term (θ^*Y) and the COMP_X term (α^*X) respectively using the Aragon (1997) approach.

Stage 2, Part 2: Plot a graph of the COMP_X dimension vs. the COMP_Y terms. Choose a functional form $g(\cdot)$ where $COMP_Y = g(COMP_X)$ such that it obtains the lowest value

³ See Naik, Hagerty and Tsai (2000) for an exhaustive comparison of SIR and popular dimension reduction techniques

on model indices such as Akaike Information Criteria (AIC). Test whether a sub-DMU's increase in efficiency significantly increases the output-mix of the media-platform.

As shown in Column 6 in Table 1 the use of our two-stage (NDEA + MSIR) technique addresses all three challenges of media-platform benchmarking. Next, we demonstrate the empirical applicability of our approach using data on U.S. print newspapers.

Empirical Illustration

Data Setting

Our data comes from the Inland Press Association (IPA). Since 1916, IPA has kept annual records of data pertaining to the financials of hundreds of U.S print newspapers. The IPA venture mainly began as a service to small and medium newspapers (daily circulation of less than 85,000) that would otherwise lack reference to industry norms. The IPA database includes data on costs incurred by various departments of a newspaper (number of employees, expenses on equipment), revenues obtained and profits generated. To maintain confidentiality, IPA does not disclose the name and location of the newspapers nor does it provide any data on newspapers that have a subscription base larger than 85,000. Notwithstanding this limitation, the IPA data still “tell us more about the economic innards of American dailies than any other source” (Blankenburg 1989, p. 98). For our analysis, we obtained data from 310 newspapers from the year 1999 to demonstrate our application. We also replicated the analysis with 225 newspapers from 2002. The newspapers are each stand-alone DMUs for the purpose of our benchmarking analysis.

The IPA database breaks down costs into *six* departments: newsroom, distribution/circulation, sales force, mail-room, administration and building facilities. However, we restrict ourselves to three departments for the purpose of this analysis, i.e. the newsroom,

distribution/circulation, and sales force. This is because a) a majority of the expenditure (about 75%) in newspaper companies is in these three departments and b) past research shows that the news, distribution and sales functions are the main operational functions of the newspapers while the others are typically subsidiary functions (Blankenburg 1989).

Input Measures

We use three input measures in each of the departments, the number of full-time employees, the number of part-time employees and expenditure on equipment.⁴

Output Measures

We use measures of output pertaining to both the readers and advertisers of the newspaper. We measure reader-side output with the pages of news content produced (in inches) and the number of subscriptions sold. We measure advertiser-side output through four measures. The first measure is the amount of ad space sold (in inches). Three other measures of advertiser-side output capture the amount of advertising revenue generated by the newspaper through the sale of local, national, and classified advertising respectively.

Table 2 presents the descriptive statistics of the outputs and inputs for the years 1999 and 2002. We note that the newsroom is the most highly staffed department with as many as 40% of the employees. Also, the distribution department contributes to a majority of the equipment expenses. On the output side, the average ratio of number of content-pages to ad-pages is similar in 1999 and 2002 (58% and 59% respectively) and in keeping with industry norms for the ratio (e.g. Peer and Nesbitt, 2004). However, large standard deviations show that there is significant variation in the norms used by individual newspaper managers. Specifically, the ratio of content

⁴ In the newsroom, this typically refers to investments in technology used to create news (e.g. computers, newswire equipment). In the distribution department, it involves vehicles and equipment and in the sales force department, this involves technology to facilitate selling (e.g. databases, communication devices)

to ad-pages varies from 0.22 to 0.85 across the years 1999 and 2002. Also, the bulk of local newspaper ad-revenue comes from ad-space purchased by retailers (52%) operating in the geographic locality of the newspaper.

Efficiency Analysis

The first step of our analysis involves performing an NDEA analysis to obtain the departmental efficiency scores. Before we perform the NDEA, we delineate the responsibility of each of the newspaper departments.

Organizational-Structure

The typical underlying network structure of a newspaper is drawn from past literature is presented in Table 3. We also consulted managers of privately owned newspaper firms to confirm this working structure. We describe the roles and outputs that each department is responsible for below:

Newsroom: The role of the employees in the newsroom is the upkeep of journalistic quality, editorial independence and integrity (Mantrala, Naik, Sridhar and Thorson 2007). Specifically, the employees and equipment in the newsroom (inputs) are dedicated to the creation of news content and a subscriber base (outputs). A majority of the news in local newspapers that have a subscription base of less than 80,000 is written by staff and not wire service (Peer and Nesbitt, 2004). The content produced by the newsroom is quite diverse, i.e. it includes stories pertaining to politics / government, sports, local entertainment, crime, community and real estate.

Past research has shown that ads sold by the newspaper are shown to influence both the number and choice of stories of the newsroom. Soley and Craig (1992) show that a majority of small newspapers feel the pressure of preparing content to parallel the theme of some of the

advertising messages in the paper. Therefore, we treat the outputs from the sales force as *linked inputs* to the newsroom in the NDEA model (see Table 3).

Distribution: The role of the employees in the distribution department is to deliver the newspaper to the reader. Delivery systems are thought of as strategic assets within the industry (Newspaper Association of America Report, 2000). Past research finds that the distribution elasticity of demand is positive and significant (Mantrala et al 2007). To the extent that delivering a newspaper on time can retain subscribers' interest in the service, the main output of the distribution department is also subscribers.

Sales force: The role of the sales force is to sell ad-space to advertisers. The total amount of space sold and the retail, national, classified revenue of the newspaper is completely within the jurisdiction of the media sales force (Warner and Buchman 1991). The majority of ads in newspapers (about 85%) promote a product or a service; the remaining ads promote events such public meetings and personal messages (Peer and Nesbitt, 2004). Past research has shown that the output produced by the newsroom (pages of content, subscriptions) and distribution departments (subscriptions) is shown to influence advertisers in buying ad space in a newspaper (Smith, 1998). We treat the outputs from these two departments as being linked inputs to the sales force in the NDEA model (see Table 3).

Step1: Results of NDEA Analysis

We obtained the efficiency scores for the NDEA model through the linear programming approach suggested by Tone and Tsutsui (2008)⁵. To test the efficacy of the NDEA model, we also compared the results against a traditional DEA model whose solutions we obtained through the Tone (2001) approach.

⁵ We used the commercially available software DEA-Solver PRO60j for this purpose

Efficacy of NDEA Over DEA

The mean efficiency scores of the newspapers in the Years 1999 and 2002 are provided in Table 4. The mean overall standard DEA efficiency produced was 0.77 for the year 1999 and 0.86 for the year 2002. In contrast, the overall NDEA efficiency was 0.53 for the year 1999 and 0.62 for the year 2002. The scores of the DEA tend to be higher than the NDEA model. In contrast, the use of NDEA results in a smaller score for each newspaper (DMU). The smaller score is reflective of the idea that NDEA is more conservative, i.e. it is able to identify more reasons to penalize DMUs for their inefficiency.

Second, we note that NDEA provides the sub-DMU efficiencies as well as the overall DMU efficiency for each firm. This is unavailable from the DEA analysis. Table 5 sheds further light on the benchmarking capability of NDEA. For a benchmarking tool to be useful, it must shed light on outstanding rather than just above-average performers. In this vein, the efficacy of a good benchmarking technique rests in its ability to single out a handful of top performers. Table 5 shows that DEA performs poorly in this regard. Specifically, 197 firms from the year 1999 and 163 firms from the year 2002 are classified as being fully efficient. Going by the sample sizes in the respective years, this analysis suggests that about 70% of the industry is fully efficient and hence worth learning from. On the other hand, NDEA suggests that 30 firms in 1999 and 22 in 2002 are fully efficient. Clearly, NDEA gives a manager a better chance to “learn from the pros” (American Society for Training and Development, 1992) since the cost of learning from a fewer set of industry practices (about 10%) is much lower and is probably more meaningful.

Third, an efficiency score would have more face validity if it is aligned with a strategically important goal of the organization, viz. profit generation. For example, while comparing two efficiency scores, it would be reasonable to assume that the better score was more highly correlated with a DMU's profits. Table 6 provides the correlations between NDEA efficiency scores of each newspaper and the newspaper's profits. We note that in both years 1999 and 2002, the NDEA score's correlation is fairly high (0.34 in 1999 and 0.32 in 2002) and statistically significant. Additionally, the correlations are much higher than the DEA scores' correlation with profits in 1999 (0.19) and 2002 (0.20) respectively.

We have therefore shown both conceptually and empirically the idea that NDEA is a better choice in Stage 1 of our benchmarking analysis, i.e. obtaining efficiency scores of media-platforms. We discuss some substantive insights stemming from the granular view that NDEA provides before moving to Stage 2.

Substantive Results for the Newspaper Industry

Referring back to Table 4, we note that on average, the newsroom is the most efficient department in the year 1999 (Mean = 0.76) as well as 2002 (Mean = 0.79), nearly 1.5 and 1.25 times larger than the other department's average efficiency scores in 1999 and 2002 respectively. This could be because the newspaper story composition is fairly standardized in the industry (Peer and Nesbitt, 2004) while media sales forces operate in a much more uncertain environment or that newsrooms experience lower levels of turnover than sales forces (e.g., 15% vs 23%, (Duke and Nesbitt, 2004. Lower turnover tends to be associated with better organizational performance (Meier and Hicklin, 2007).

Next, Table 7 shows that the overall industry has a mean efficiency score of 0.53 in 1999 and 0.63 in 2002, while 15% of the sample in 1999 and 8% of the sample in 2002 were operating

at efficiency scores below 25%. In contrast, 23% of the firms in 1999 and 34% of the firms in 2002 were operating above 80%. It is likely that cutbacks in various newspaper departments during the 1999-2002 period resulted in higher efficiency scores in 2002. (Meyer, 2004),

Finally, Table 8 shows that firms performing on the efficient frontier, i.e. firms with a 100% NDEA score are significantly more profitable than inefficient firms in both years.

Why are some newspapers more efficient than others?

To shed light on some covariates of high efficiency, we performed a cluster analysis of the NDEA efficiency scores obtained from the 1999 and 2002 NDEA analysis. Specifically, we pooled the results of the three departmental efficiency scores (newsroom, distribution and sales force) of each newspaper with seven profiling variables created from the IPA dataset:

1. Number of issues published per year
2. Number of staff in the mailroom
3. Number of staff involved in general and administrative duties
4. % total employees hired part-time (vs. full-time)
5. % of total ad-revenue acquired as national ad revenue
6. % of pages occupied by content (vs. ad space)
7. % of total revenue generated by content (vs. ads)

Variable 1 serves as a proxy for whether the newspaper is a daily newspaper or publishes more than one daily a year. Variables 2 and 3 (staff) are proxies for the human-resource endowments that a newspaper possesses; Variables 4 through 7 represent strategic choices that a newspaper makes with respect to employees (Variable 4), and newspaper composition. We then performed a cluster analysis of the 7 profiling variables together with the 3 departmental efficiency scores

The results of the cluster analysis for the Years 1999 and Year 2002 are shown in Table 9 and Table 10. Based on the Bayesian Information Criterion (BIC) indices in Table 9 and the parsimony of the two cluster solution, we retained the two-cluster solution. From Table 10, we can see that Cluster 2 possesses much higher values of newsroom, distribution, and sales force efficiencies than the other cluster. Specifically, as shown in Table 10, the mean values of the newsroom, distribution and sales force efficiency were 0.95, 0.74 and 0.92 respectively in Cluster 2 (Year 1999) as compared to 0.67, 0.46 and 0.27 in Cluster 1 (Year 1999). Cluster 2 also has uniformly higher departmental scores in the Year 2002. We denote Cluster 2 to be the “*High Efficiency*” cluster and Cluster 1 to be the “*Low Efficiency*” cluster. Focusing on the profiling variables that show pronounced differences across the *High Efficiency* and *Low Efficiency* clusters we note:

First, the numbers of mailroom and administrative staff is much higher in the *High Efficiency* cluster compared to the *Low Efficiency* cluster. For example in the year 1999, while there are about 12 and 18 mailroom and administrative staff respectively in the *High Efficiency* cluster on average, there are only about 8 and 11 in the *Low Efficiency* cluster in 1999. This also holds true in 2002. This indicates that the more efficient newspapers are generally the ones that are better endowed with support staff.

Second, the *High Efficiency* clusters in 1999 and 2002 have a *lower* ratio of part-time employees to total employees. Part-time employees are quite common in the United States and constituted about 20% of the workforce in 2001 (Bureau of Labor Statistics, 2001). Part-time jobs have expanded primarily because more employers view them as a means to cut labor costs. However, part-time employees have also shown to report lower organizational commitment since they feel less included in the workplace (Katz & Kahn, 1979). In the case of newspapers, it is

possible that the cost-saving benefit of part-time employees is overridden by the lack of productivity induced due to lower commitment. Our finding suggests that shifting the work-balance so as to have more full-time employees might be related to achieving organizational efficiencies.

Third, we find that the *High Efficiency* cluster produces a lower percentage of content and generates a lower percentage of total revenue from subscriptions than the *Low Efficiency* cluster. For example in the Year 2002, the High Efficiency cluster fills 58% of its newspaper with content while the Low Efficiency cluster fills 61%. This is interesting since it suggests that falling *short* of the popularly noted industry heuristics of the 2/1 content to ad-space ratio is correlated with higher efficiencies (Peer and Nesbitt, 2004). One explanation for this is that US readers of local newspapers are shown to be ad-lovers, i.e., attracted to newspapers with more advertising (Sonnac, 2002, Mantrala et al 2007). Bhargava and Feng (2009) show that the optimal proportion of ad to content levels *increases* with *decreasing* sensitivity of consumers to ads, given that advertising margins are typically much higher than subscription margins. It follows that the more efficient (and hence more profitable ones) newspapers operate at a lower ratio of news content to ad space than less profitable ones.

Thus, three useful differentiating traits of department efficiency in newspapers include the presence of support staff, the presence of more full-time employees and a larger share of space devoted to advertising.⁷

⁷ As we are restricted to data from a syndicated source, we could not study more than 10 traits across newspapers. However, cluster-analysis applied to data from a single firm owning many DMUs could provide more traits information pertaining to the demographic characteristics of the geographic locations of the DMUs. We identify this as a further research opportunity.

Stage 2: Results of MSIR Analysis

Stage 2 involves a statistical estimation of how the inputs in each department together with the department efficiencies impact the outputs produce by the media-firm. The first step condenses the dependent and independent variable vectors into composite Y (COMP_Y) and composite X (COMP_X) directions respectively using MSIR. In the media-platform example, the dependent variable vector is the set of 6 outputs (pages of content, pages of ad space, subscriptions, retail, local and classified ad revenue). The independent variable vector is the set of 3 inputs (full-time and part-time employees, investments in equipment) in each of the 3 departments and the 3 departmental efficiency scores. Therefore, the independent variable vector has $(3 \times 3) + 3 = 12$ components.

We then graph the estimated COMP_Y and COMP_X directions using a scatter-plot to examine their relationship and choose an appropriate functional form to characterize their relationship. In the media-platform example, we found that the best-performing model was given by the functional form

$$\text{COMP_Y} = \beta (\text{COMP_X})^\delta / \delta \quad (7)$$

where $\delta=0.6$ [Year 1999] and $\delta=0.5$ [Year 2002] was chosen on the basis of Akaike-Information Criterion (AIC). We direct the reader to the Technical Appendix (D) for a note on how we found the best-fitting functional form and confirmed the efficacy of the MSIR approach over the Arnold et al (1996) approach. Table 11 present the results of the MSIR model and the estimates of β from the regression of COMP_Y and COMP_X⁸

To obtain a meaningful interpretation of the results in Table 11, we used the estimates in the model to calculate a mathematical expression for the % increase in a newspaper output (e.g.

⁸ We adapted the code provided by Aragon et al (1995) for the implementation of MSIR. We ran the GAUSS code on GAUSS 7.0

ad space sold) given a 1% change in a department's efficiency. Since the expression is a multivariate function of random variables, we used the delta method to calculate the standard error and t-value of the expression (Davidson and MacKinnon 2004, p. 202)

We find that at the current levels, an incremental increase in newsroom efficiency does not statistically impact any of the 6 outputs that the newspaper produces. This could be because first, the operating levels of newsroom efficiency are already 20-30% higher than the efficiencies of the distribution and sales force departments and there are diminishing returns to efficiency increases. Second, newspapers tend to be under-staffed in the newsroom (Mantrala et al 2007, Meyer and Kim 2004) and the average newsroom in our database is already performing as efficiently as it can, given its limited staff.

In contrast, Table 12 indicates that an increase in sales force efficiency can lead to a significant increase in the outputs of the newspaper. Some ways of increasing sales force efficiency in media selling practices include gathering accurate and timely information on customer reach, and market share of the newspaper that can be presented to the retailer (Warner and Buchman 1991 p 160).

Table 12 also indicates that an increase in salesforce efficiency is likely to have the largest impact on the subscriptions to the newspaper, pages of content produced and the classified ads sold by the paper. Thus adopting a buyer-initiated information revelation format for sales presentations may enhance selling efficiency (e.g., Bharadwaj, Chen and Godes 2008).

Also, selling ads pertaining to content might enable the newsroom to generate more content. For example, stories on local sports activities enables a newsroom to generate stories that identifies better with the local community; this is well-supported by retailers that are able to

access specific target audiences (Warner and Buchman 1991). Overall, increases in sales force efficiencies benefit the entire set of outputs produce by the newspaper.

Finally, Table 12 also shows that average distribution efficiencies can result in the generation of more output by the newspaper. Specifically, some high impacts of distribution efficiency were on subscriptions and selling classified ads. Naturally, receipt of the newspaper on time increases the utility of the reader to stay subscribed or place ads in the paper.

In summary our results based on statistical inference establish methodological and substantive insights about the benchmarking of media-firms. Our results show that our proposed 2 Stage NDEA +MSIR method does better than existing methods in addressing the benchmarking challenges of media-firms. Our results also shed substantive light on the levels of efficiency, covariates of high efficiency and the statistical impact of high efficiency on the outputs produced by newspapers.

Discussion and Conclusions

Productivity benchmarking is a critical responsibility of managers since accurate and timely benchmarks are useful in identifying best-practices of companies. However, the literature so far has largely ignored the benchmarking problem of a burgeoning class of firms, media-platforms operating in two-sided markets like newspaper firms that face tough economic questions. These firms pose novel challenges for benchmarking. Our first research contribution is to develop a suitable methodology and demonstrate its efficacy in benchmarking media-platforms. Our second contribution is to apply the methodology to better understand efficiencies in the U.S. local newspaper industry.

Many media-firms produce a joint product that is simultaneously consumed by two end-user groups: consumers and advertisers. In this type of business, the outputs produced by one department can greatly impact the efficiency of the other and vice versa. Our benchmarking methodology embraces this two-sided feature while providing departmental and overall efficiency scores and department-level insights. Therefore, managers can use our two-stage approach to benchmark media-platforms and in process development efforts that follow.

Apart from media-platforms, our research also contributes to the literature on benchmarking. While the challenges posed by media firms were the main reasons that led to the development of our hybrid approach, we note that it is completely general in its application. Specifically, the NDEA functionality allows several different networked organizational structures (e.g. Tone and Tsutsui 2008) while the SIR functionality allows several different production functional forms (e.g. Naik, Hagerty and Tsai 2000) to be incorporated into benchmarking analysis. Our approach can thus be used for benchmarking in operations, management, social sciences as well as transportation research.

Our approach has several other applications in the marketing context. Many complex marketing organizational issues such as sales-marketing disconnect can be studied with our approach. For example, many organizations have a dispute over whether the advertising or personal selling function is more efficient. The role of the advertising department is usually to generate leads that the sales people follow-up on, i.e. the selling process is networked. While the sales personnel claim that the advertising personnel do not generate enough leads, advertising personnel complain that the sales personnel do not follow through and convert the leads (Smith, Gopalakrishna and Chatterjee 2006). Our benchmarking process can be used to identify (with statistical inference) which of the processes (lead-generation, lead-conversion) in the “sales

funnel” is more efficient and hence be useful in benchmarking in an integrated marketing communications setting.

From our empirical analysis of the hundreds of firms in the newspaper industry, we summarize the takeaways succinctly. First, we find that the newsroom department seems to be the most efficient of the three main departments in the newspaper. Second, we find that newspapers that are more efficient are also much more profitable. Third, we find that lower part-time employee percentages, higher ratios of number of support and administrative staff, higher ad-space percentages and lower circulation revenue percentages tend to co-vary with newspapers that are highly efficient. Lastly, we find that at their current levels, newsroom efficiency increases do not statistically increase outputs of the newspapers. However, being able to increase the efficiency of the sales force and distribution departments increases reader-side output (subscriptions) as well as advertiser-side output (classified ads).

Future research should therefore extend our work to other media-settings such as television, radio etc. Additionally, the issues of dynamics of efficiencies and allocative efficiencies within this two-sided market setting pose additional unresolved research questions that may be fruitful to pursue. Notwithstanding these extensions, we hope the results of our research are useful to academics and practitioners alike.

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Appendix A. Obtaining Efficiency Scores through DEA

We describe the *slacks-based* approach (due to Tone [2001]) to measure efficiency. The slacks-based measure is quite popular since it produces a scalar efficiency score that is *invariant* with respect to the units of measurement used for inputs or outputs. The efficiency score (ρ) is obtained as follows. Consider n DMUs that each use m inputs to produce s outputs each. The input-vector of a particular DMU is given by (x_0, y_0) . The firm's production possibility set, or the set of feasible production improvement possibilities is represented as (Cooper, Seiford and Tone, 2006)

$$P = \{ (x, y) \mid x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0 \} \quad (\text{A1})$$

where λ is assumed to be a non-negative vector. This means that for any activity (x, y) , any activity (\bar{x}, \bar{y}) with $\bar{x} \leq x$ and $\bar{y} \geq y$ is allowed to be in the production possibility set. To capture variable returns to scale, we specify

$$\sum_{i=1}^n \lambda_i = 1 \quad (\text{A2})$$

A DMU's input-output vector (x_0, y_0) is given as

$$x_0 = X\lambda + s^- \quad (\text{A3})$$

$$\text{and } y_0 = Y\lambda + s^+ \quad (\text{A4})$$

where s^- is called the input excess slack and the s^+ is called the output shortfall that capture how a DMU is falling short of a fully efficient DMU. An SBU's efficiency score (ρ) is given by

$$\rho = \frac{1 - (1/m) \sum_{i=1}^m s_i^- / x_{io}}{1 + (1/s) \sum_{r=1}^s s_r^+ / y_{ro}} \quad (\text{A5})$$

DEA scores are calculated by finding the weights that allow a DMU to maximize its efficiency score relative to all other DMUs subject to the constraint that no DMU can have an efficiency score greater than 1. Specifically, the score is obtained by the solution of the optimization problem given by

$$\text{Min}_{\{\lambda, s^+, s^-\}} \rho = \frac{1 - (1/m) \sum_{i=1}^m s_i^- / x_{io}}{1 + (1/s) \sum_{r=1}^s s_r^+ / y_{ro}} \quad (\text{A6})$$

s.t. Equations A3, A4 and where $\lambda \geq 0, s^- \geq 0, s^+ \geq 0$. The solution to the problem provides optimal measures for λ^*, s^{+*} and s^{-*} and the minimized objective function value ρ^* for a DMU. A DMU is 100% efficient when ρ^* is 1. This is the same as saying that both slack values are 0.

Appendix B. Obtaining Efficiency Scores through NDEA

Consider a setting with n DMUs ($j=1, \dots, n$) consisting of K sub-DMUs ($k=1, \dots, K$) each. Let \underline{m}_k and \underline{r}_k be the numbers of inputs and outputs respectively that sub-DMU k is responsible for. Let the input vector be denoted by x_j^k and the output vector be given by y_j^k . In addition, suppose that sub-DMU k provides some outputs that sub-DMU h uses as inputs. We denote those outputs as the linked output vector denoted by $z_j^{(k,h)}$. The production possibility set $\{(x^k, y^k, z^{(k,h)})\}$ for a sub-DMU k belonging to a DMU j is given by

$$x^k \geq \sum_{j=1}^n x_j^k \lambda_j^k \quad \forall k = (1, 2, \dots, K) \quad (\text{B1})$$

$$y^k \leq \sum_{j=1}^n y_j^k \lambda_j^k \quad \forall k = (1, 2, \dots, K) \quad (\text{B2})$$

$$z^k \geq \sum_{j=1}^n z_j^{(k,h)} \lambda_j^k \quad \forall (k, h) \text{ (as outputs from } k \text{ to other sub-DMU's)} \quad (\text{B3})$$

$$z^k = \sum_{j=1}^n z_j^k \lambda_j^k \quad \forall (k, h) \text{ (as inputs to } h \text{ from sub-DMU } k) \quad (\text{B4})$$

$$\sum_{j=1}^n \lambda_j^k = 1 \quad \forall (k, j) \quad (\text{B5})$$

$$\lambda_j^k > 0 \quad \forall (k, j) \quad (\text{B6})$$

where weights are (λ^k) for each sub-DMU are to be determined. The key addition to the production possibility set from the idea of DEA is the linked output vector $z^{(k,h)}$. Specifically, a sub-DMU can produce an output that is used by another department to produce its own outputs or use the output of another department to produce its own outputs. This adds two equations pertaining to the linked vector to the production possibility set of the NDEA compared to the DEA approach (see C3 and C4). The efficiency score for a sub-DMU (ρ_k) is then given by

$$\rho_k = \frac{1 - (1/m_k) \sum_{i=1}^m s_i^{k-} / x_{io}^k}{1 + (1/r_k) \sum_{r=1}^s s_r^{k+} / y_{ro}^k} \quad (\text{B7})$$

And the DMU's overall efficiency scores across all sub-DMUs is given by

$$\rho = \frac{\sum_{k=1}^K 1 - (1/m_k) \sum_{i=1}^m s_i^{k-} / x_{io}^k}{\sum_{k=1}^K 1 + (1/r_k) \sum_{r=1}^s s_r^{k+} / y_{ro}^k} \quad (\text{B8})$$

For any given sub-DMU, the input-output vector (x_0^k, y_0^k) is given as

$$x_o^k = X^k \lambda^k + s^{k-} \quad (\text{B9})$$

$$y_o^k = Y^k \lambda^k - s^{k+} \quad (\text{B10})$$

The terms s^{k-} and s^{k+} represent the input excess and output shortfall slack for each sub-DMU and $s^{k-} \geq 0, s^{k+} \geq 0$. Finally, an additional constraint is introduced to add the linked outputs

$$Z^{(k,h)} \lambda^h = Z^{(k,h)} \lambda^k \quad (\text{B11})$$

where $Z^{(k,h)} = (z_1^{(k,h)}, z_2^{(k,h)}, \dots, z_n^{(k,h)})$. To solve for sub-DMU and DMU efficiency, the weights for each sub-DMU and slack values are determined by allowing the firm to be as efficient as possible given its constraints. This is similar to the idea of DEA except that it is carried out for each sub-DMU within a DMU. More specifically, the following optimization problem is solved

$$\frac{\text{Minimize}}{\{\lambda^k, s^{k+}, s^{k-}\}} \rho_0 = \frac{\sum_{k=1}^K 1 - (1/m_k) \sum_{i=1}^m s_i^{k-} / x_{io}^k}{\sum_{k=1}^K 1 + (1/s_k) \sum_{r=1}^s s_r^{k+} / y_{ro}^k} \quad (\text{B12})$$

subject to constraints (B9), (B10) and (B11). Solving the problem yields ρ_0^* which is the overall efficiency score of a DMU. It also yields sub-DMU efficiency scores ρ_k^* for each sub-DMU from (B7).

Appendix C. Univariate Sliced Inverse Regression (SIR) and Multivariate Sliced Inverse Regression (MSIR): Obtaining the dimension-reduced space

Univariate Sliced Inverse Regression

The basic representation of a univariate SIR model is

$$y = g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \quad (C1)$$

where y is a uni-variate vector of n observations ($n \times 1$), $g(\cdot)$ is an unknown function, X is a p dimensional matrix of n observations ($n \times p$), α is a $(k \times p)$ matrix vector of coefficients ($k < p$) and ε is the errors term about which no distributional assumption is made. The combination of the k alpha vectors is known as the effective dimension reduction (EDR) space and helps us better understand the relationship between y and the vector X by condensing it into a smaller sub-space. For example, if only one dimension is needed to reduce the vector X , the EDR space has only 1 α vector. The α vector(s) are obtained through using information on the conditional distribution of X given Y , thereby reversing the conventional view (of forward regression). Specifically, we first define a function $\varphi(\cdot)$, denoted to be the *inverse regression function* as

$$\varphi(y) = E[x|y] \quad (C2)$$

Next, we define the matrix

$$\Sigma_\eta = \text{cov}(E[x|y]) \quad (C3)$$

The function $\varphi(y)$ is in p -dimensional space and the task in SIR is to reduce it to k -dimensional space. To do this, let $\alpha_1, \dots, \alpha_k$ be defined as $p \times 1$ vectors of coefficients. We then obtain the value of the α vectors by the Eigen decomposition of Σ_η with respect to the covariance matrix Σ_X .

Specifically, it can be obtained from the following equations

$$\Sigma_\eta \alpha_k = \lambda_k \Sigma_X \alpha_k \quad (C4)$$

$$\lambda_1 > \lambda_2 > \dots > \lambda_p \quad (C5)$$

$$\alpha_k' \Sigma_X \alpha_k = 1 \quad (C6)$$

Where λ_k is the k^+ Eigen-value, arranged in descending order for $k=1, \dots, K$ and α_k is the corresponding Eigen-vector. To obtain actual estimates of $\hat{\alpha}_k$ by using the given data form X and Y , we need a sample estimate of the covariance matrix Σ_η . We can obtain this value by a procedure that sorts the X matrix according to the values in Y , partitions the sorted X matrix into

H slices and computes the mean of the independent variables in each slice as \bar{X}_h where $h=1, 2, \dots, H$. the exact expression for the estimated value of Σ_η is given as

$$\hat{\Sigma}_\eta = \sum_{h=1}^H \hat{p}_h (\bar{X}_h - \bar{X})(\bar{X}_h - \bar{X})' \quad (C7)$$

Where \hat{p}_h is the proportion of observations falling into slice h . The exact computation algorithm to slice the data is given in Naik, Hagerty and Tsai (2000, p 100). We can replace the estimate of

Σ_η from (C7) and the sample covariance matrix Σ_X to obtain the estimates of $\alpha_1, \dots, \alpha_K$ in C4-C6. The estimates values are consistent and not sensitive to the number of slices (Li 1998). We can also obtain the asymptotic standard error of α from the expression (Chen and Li 1998, p 297) as

$$\text{Standard err}(\hat{\alpha}) = \frac{(1 - \hat{\lambda}_k)}{\hat{\lambda}_k} n^{-1} \hat{\Sigma}^{-1} \quad (\text{C8})$$

Multivariate SIR (MSIR)

The MSIR (also known as Alternating SIR (ASIR) is represented as

$$Y = g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \quad (\text{C9})$$

where $g(\cdot)$, X , ε , α and k are defined just like in SIR but Y is a q dimensional vector of n observations. The goal in MSIR is to reduce the dimensionality of Y and X in an alternating fashion (Li et al 2003). First, similar to the k dimensional EDR space of X ($k < p$), an l -dimensional sub-space of Y (called the most-predictable Y space or MP space Y) is defined ($l < q$). The MSIR model is represented as

$$\begin{aligned} \theta_1 Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \\ \theta_2 Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \\ &\dots \\ \theta_l Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \end{aligned} \quad (\text{C10})$$

where the Y vector is reduced into l dimensions and θ is a $(l \times q)$ vector. The values of θ and α are found by running SIR in an alternating fashion on X and Y respectively. Specifically, the iterative procedure outlined in Li et al (2003) is as follows

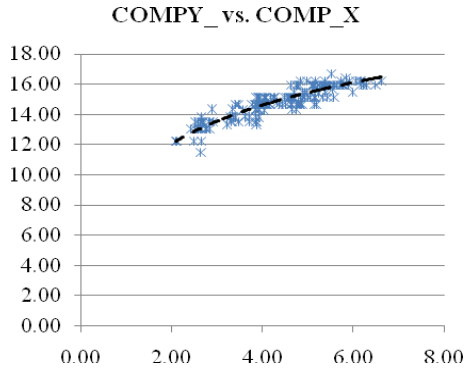
1. Conduct a canonical correlation analysis between X and Y .
2. Use the first canonical variate of Y to lower the dimension of Y tentatively.
3. Apply SIR to the reduced Y for finding EDR directions for X (use procedure describe under “*Univariate SIR*” in the same Appendix)
4. Use the SIR variates of X to find the MP variates of Y .
5. Use the MP variates to reduce the dimension of Y .
6. Return to step 3 until there is little change in the results.

The first canonical covariate usually explains a fair portion of the variance in the Y vector and can be used to reduce Y (Step 2). Canonical correlation itself is simply a special case of univariate SIR. The canonical variates of Y begin the iterative process of reducing X and Y respectively through the SIR procedure above (Step 3 to Step 5). Step 6 can be defined as changes in estimates of numerical order less than 10^{-5} . Similar to SIR, a) we can obtain the values of the asymptotic standard error of the EDR space, b) the MSIR estimates θ and α is not sensitive to the number of slices of X and Y respectively and c) we can subsequently choose any functional form $g(\cdot)$ to represent the relationship between the condensed Y space and the condensed X space.

Appendix D. Efficacy of MSIR over the Arnold et al (1996) approach

To perform MSIR in our example, we first transformed the outputs and inputs into natural logarithms. By doing so, we assumed a Cobb-Douglas relationship between outputs and inputs. We then obtained the COMP_Y and COMP_X directions. Upon examining the plots, the relationship between COMP_Y and COMP_X directions was still non-linear. For example, the plot for the COMP_Y space versus the COMP_X space for the Year 1999 is given below.

Figure D1. Plot of COMP_Y vs. COMP_X Space



This shows that transforming the outputs and inputs into logarithms did not capture all the non-linearity in the production function, i.e. the Arnold et al (1996) approach would not suffice.

To ascertain that there is some more non-linearity, we estimated a series of non-linear models given by $COMP_Y = \delta \cdot COMP_X$ where δ ranged from 0 to 1 in increments of 0.1. When $\delta = 1$, the relationship between COMP_Y and COMP_X is linear and we can retain the Arnold et al (1996) assumption. However, we found that the AIC minimizing value of δ was 0.6 in the year 1999 and 0.5 in the year 2002 (see Table D1 below).

Table D1. Model Comparison

δ	AIC-c (1999)	AIC-c (2002)
0 (Log)	1188.24	671.46
0.1	1677.26	1132.64
0.2	1560.08	1030.22
0.3	1425.51	907.57
0.4	1277.68	769.68
0.5	1144.89	669.29
0.6	1099.6	707.56
7	1180.7	833.06
0.8	1321.89	966.92
9	1464.25	1076.52
1 (Linear)	1590.47	1167.67

Clearly, the extra non-linearity does a better job of explaining the relationship between outputs and inputs. Therefore, using the MSIR approach gives us the flexibility to choose any level of non-linearity that is suitable for our model and it performs better than a simple Cobb-Douglas approach.

Table 1. Comparison of Benchmarking Techniques

Methodological Issue	DEA	NDEA	SFA	Two-Stage (DEA + OLS)	Two-Stage (NDEA + MSIR)
Produces efficiency scores at the department-level?	Yes, but not with connectedness	Yes	Yes, but not with connectedness	Yes, but not with connectedness	Yes
Recognizes that some departments' outputs are mutually inter-linked?	No	Yes	No	No	Yes
Capable of statistical inference about the impact of efficiency?	No	No	Yes, with functional form assumed apriori	Yes, with Cobb-Douglas functional form	Yes

Table 2. Descriptive Statistics

		Year 1999		Year 2002	
Variable	Notation	Mean	Std Dev.	Mean	Std Dev.
<i>INPUT MEASURES</i>					
Newsroom- Full time Employees (#)	NFE	32	22	36	24
Newsroom- Part time Employees (#)	NPE	3	4	4	11
Newsroom- Expenses on Equipment (\$)	NEQ	335854	247635	383207	274002
Sales force- Full time Employees (#)	ADFE	26	21	27	17
Sales force- Part time Employees (#)	ADPE	2	3	2	7
Sales force- Expenses on Equipment (\$)	ADEQ	292641	334508	348541	431215
Distribution- Full time Employees (#)	DFE	16	14	18	17
Distribution- Part time Employees (#)	DPE	8	11	8	14
Distribution- Expenses on Equipment (\$)	DEQ	742971	731874	962721	1018622
<i>OUTPUT MEASURES</i>					
Variable	Notation	Mean	Std Dev.	Mean	Std Dev.
Pages of Content Produced (#)	CONPAGES	6916	2903	7715	3150
Retail Ad Revenue Generated (\$)	RETAIL	4417502	6987257	4394404	3435720
National Ad Revenue Generated (\$)	NATIONAL	249378	363728	360457	665971
Classified Ad Revenue Generated(\$)	CLASS	3592898	3626875	3950905	3726696
Pages of Ad Space sold (#)	ADPAGES	4993	2918	5125	2716
Number of Subscriptions sold (#)	SUB	26417	18426	28966	18979

Table 3. Newspaper Organizational Structure for NDEA model

Quantities	Newsroom	Distribution	Sales force
Inputs	Full time Employees (#)	Full time Employees (#)	Full time Employees (#)
	Part time Employees (#)	Part time Employees (#)	Part time Employees (#)
	Expenses on Equipment (\$)	Expenses on Equipment (\$)	Expenses on Equipment (\$)
Outputs	Subscriptions sold (#)	Subscriptions (#)	Pages of Ad Space (#)
	Pages of Content (#)		Retail Ad Revenue (\$)
			National Ad Revenue (\$)
			Classified Ad Revenue (\$)
Linked quantities obtained from newsroom	-NA-		Subscriptions (#)
			Pages of Content Produced (#)
Linked quantities obtained from Distribution	-NA-		Number of Subscriptions (#)
Linked quantities obtained from Salesforce	Pages of Ad Space (#)		-NA-
	Retail Ad Revenue (\$)		
	National Ad Revenue (\$)		
	Classified Ad Revenue (\$)		

Table 4. DMU and sub-DMU Mean Efficiency Scores

Efficiency Score	Year 1999		Year 2002	
	DEA	NDEA	DEA	NDEA
Overall DMU Efficiency (Mean)	0.770	0.5291	0.855	0.625
Newsroom sub-DMU Efficiency (Mean)		0.7584		0.788
Distribution sub-DMU Efficiency (Mean)		0.5477		0.603
Sales force sub-DMU Efficiency (Mean)		0.4835		0.613

Table 5. DMU's Classified as 100% Efficient

Year	DMUs classified	DMUs classified	Sample Size
	100% efficient (DEA)	100% Efficient (NDEA)	
1999	197	30	310
2002	163	22	225

Table 6. Correlation with Profits

Year	Year 1999		Year 2002	
	DEA	NDEA	DEA	NDEA
Correlation with Profits	0.19	0.34	0.201	0.315
P-value	<0.01	<0.01	<0.05	<0.05

Table 7. Distribution of Good and Bad Performers

Category	Year 1999	Year 2002
Overall DMU Efficiency (Mean)	0.529	0.625
Sample Size	310	225
# Firms 80% or above (%)	72	78
# Firm 25% or below	47	19

Table 8. Profits of Top-Performers

Year	1999	2002
Profits of firms with 100% efficiency	\$4.7 mill	\$4.44 mill
Profits of other firms	\$2.70 mill	\$2.44 mill

Table 9. BIC Values for the Cluster Analysis

Panel 1. Year 1999		
<i>Number of Clusters</i>	<i>Schwarz's Bayesian Criterion (BIC)</i>	<i>BIC Change</i>
1	2258.48	
2	2029.30	-229.18
3	1991.34	-37.97
4	1990.54	-0.79

Panel 2. Year 2002		
<i>Number of Clusters</i>	<i>Schwarz's Bayesian Criterion (BIC)</i>	<i>BIC Change</i>
1	1655.88	
2	1508.01	-147.86
3	1450.53	-57.49
4	1489.46	38.93

Table 10. Cluster Analysis Results*Panel 1. Year 1999*

Categories	Cluster 1 Mean	Cluster 2 Mean	Overall
Newsroom Efficiency	0.67	0.95	0.76
Distribution Efficiency	0.46	0.74	0.55
Sales force Efficiency	0.27	0.92	0.48
Number of Issues Per Year	341.23	352.66	344.95
Mailroom Staff	8.32	11.74	9.44
Administrative Staff	10.83	18.89	13.46
% total employees hired part-time (vs. full-time)	13.99	11.31	13.12
% of total ad-revenue acquired as national ad revenue	0.03	0.03	0.03
% of pages occupied by news content (vs. ad space)	0.62	0.58	0.59
% of total revenue generated by content (vs. ads)	0.26	0.24	0.25
Sample	209	101	310

Panel 2. Year 2002

Categories	Cluster 1 Mean	Cluster 2 Mean	Overall
Newsroom Efficiency	0.62	0.95	0.79
Distribution Efficiency	0.46	0.75	0.60
Sales force Efficiency	0.32	0.90	0.61
Number of Issues Per Year	345.01	348.37	346.69
Mailroom Staff	7.07	11.88	9.47
Administrative Staff	12.43	17.96	15.19
% total employees hired part-time (vs. full-time)	14.44	10.02	12.23
% of total ad-revenue acquired as national ad revenue	0.56	0.54	0.55
% of pages occupied by content (vs. ad space)	0.62	0.60	0.61
% of total revenue generated by content (vs. ads)	0.25	0.23	0.24
Sample	113	112	225

Table 11. MSIR Estimation Results

Panel 11.1 MSIR Estimates

Inputs	Year 1999			Year 2002		
	EDR Estimates	Std. Err.	t-value	EDR Estimates	Std. Err.	t-value
Newsroom- Full time Employees (#)	0.227	0.056	4.029	0.288	0.054	5.317
Newsroom- Part-time Employees (#)	0.042	0.034	1.255	0.017	0.033	0.508
Newsroom- Expenses on Equipment (\$)	0.230	0.052	4.416	0.089	0.051	1.743
Distribution- Full time Employees (#)	0.131	0.046	2.821	0.140	0.043	3.228
Distribution- Part-time Employees (#)	0.044	0.025	1.722	0.022	0.024	0.919
Distribution- Expenses on Equipment (\$)	0.116	0.034	3.469	0.156	0.032	4.897
Salesforce- Full time Employees (#)	0.196	0.052	3.742	0.417	0.051	8.271
Salesforce- Part-time Employees (#)	0.042	0.035	1.193	0.078	0.036	2.175
Salesforce- Expenses on Equipment (\$)	0.211	0.034	6.284	0.146	0.031	4.727
Newsroom Efficiency	0.097	0.103	0.938	-0.027	0.076	-0.356
Distribution Efficiency	0.166	0.049	3.405	0.106	0.043	2.450
Sales force Efficiency	0.206	0.048	4.298	0.278	0.045	6.173
Outputs	MPY Estimates			MPY Estimates		
Pages of Content Produced (#)		0.373			0.104	
Number of Subscriptions sold (#)		0.390			0.362	
Retail Ad Revenue Generated (\$)		0.083			0.214	
National Ad Revenue Generated (\$)		0.045			0.100	
Classified Ad Revenue Generated(\$)		0.305			0.351	
Pages of Ad Space sold (#)		0.126			0.034	

Panel 11.2. Estimates from the MPY-EDX model

Coefficient	Year 1999 ($\delta=0.6$)			Year 2002 ($\delta=0.5$)		
	Estimate	Std Error	t-value	Estimate	Std Error	t-value
β	3.854	0.005	755.590	5.133	0.007	740.280

Table 12. Estimates of Impact of Efficiency on Output Variables

(Calculated at Average Efficiency Levels)

Year 1999	CONPAGES	SUB	RETAIL	NATIONAL	CLASS	ADSPACE
Distribution Efficiency	0.0253*	0.0265*	0.0057*	0.0031*	0.0207*	0.0086*
Sales force Efficiency	0.0556*	0.0582*	0.0124*	0.0067*	0.0455*	0.0188*

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