

OPTIMAL MARKETING BUDGETING AND
BENCHMARKING OF PLATFORM FIRMS

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ABSTRACT

Platform firms are firms that increase social surplus by (1) catering to distinct groups of customers such that (2) members of at least one group wish to access the other group and (3) facilitating group-access more efficiently than bi-lateral relationships between the members of the groups. Examples include markets of print media companies like newspapers and magazines (readers and advertisers), TV broadcasters (viewers and advertisers), shopping malls (shoppers and retailers), and payment cards (cardholders and merchants). The marketplace today is abundantly populated with such platform firms that operate in ‘*two-sided*’ markets. A platform firm is different from firms operating in ‘one-sided’ classic firm markets because their marketing strategies must take into account the fact that the benefit enjoyed by a member of one group depends upon how well the platform attracts customers from the other group. The marketing literature has largely ignored this aspect to date; hence platform firms remain an under-studied phenomenon in our field.

This dissertation deals with two fundamental responsibilities of marketing managers; a) setting marketing budgets optimally and b) benchmarking the performance of individual decision making units (DMUs). In two essays, this dissertation advances

knowledge with respect to optimal marketing budgeting by platform firms (Chapter 2) and benchmarking of platform DMUs (Chapter 3).

The first essay (Chapter 2) makes three contributions. We note that sales-response models in the platform-firm context must capture the notion that the benefit enjoyed by a member of one group depends upon how well the platform firm attracts members from another group, i.e., the extent of cross-market effects (CMEs). CMEs are absent in “one-sided” markets. The first contribution of the essay is a demonstration of how CMEs theoretically impact optimal investment levels and allocation ratios, extending and even reversing the extant normative budgeting rules obtained from models that ignore CMEs. The second, contribution lies in empirical demonstration of CMEs and showing how they affect the evaluation of marketing elasticity in a real-world setting. The third contribution is the development of a tool that allows a platform manager to set budgets optimally for any planning horizon by taking CMEs into account.

The second essay (Chapter 3) is focused on media-based platform firms and makes two contributions. We note that productivity benchmarking involves the study of which DMU is more efficient in converting inputs into outputs. Benchmarking media-platform DMUs poses some methodological challenges by virtue of their business model. For instance, the outputs of some platform-firms are inherently *networked* since the outputs of some departments may serve as inputs to the other and vice versa. A survey of the literature suggests that none of the current benchmarking approaches account for all of the media-platform’s benchmarking challenges simultaneously. The first contribution of this essay (Chapter 3) is to combine relatively new techniques in the operations research and statistics literatures to develop a new procedure to benchmark media-

platforms that addresses the challenges. The second contribution of the essay lies in empirical demonstration/validation of the approach via an application to U.S. print newspaper firms. While doing so, the essay also demonstrates how the developed approach outperforms applications of the existing approaches.

Thus, this dissertation offers insights into how to approach marketing budgeting and benchmarking decisions differently as platform-firm managers.

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CHAPTER I: INTRODUCTION

I. 1. Platform Firms: A Pervasive and Under-Researched Area

Much of basic marketing theory relates to settings that involve a firm offering a product/service to one or more end-user groups who, however, do not interact and transact with each other. However, there is very little research in marketing on the normative and managerial issues pertaining to a pervasive and important class of firms in the economy, namely, *platform* firms that do business in *'two-sided'* markets. The key feature of platform-firm markets, distinguishing them from the 'one-sided' classic firm markets treated in much of the previous literature, is that they have two or more different groups of customers (end-users of their products or service offerings) that businesses have to get and keep on board to succeed (Rochet and Tirole, 2005). Examples include markets of print media companies like newspapers and magazines (readers and advertisers), TV broadcasters (viewers and advertisers), shopping malls (shoppers and retailers), and payment cards (cardholders and merchants). More specifically, platform firms can increase social surplus when three necessary conditions are true: (1) distinct groups of customers exist; (2) members of at least one group wish to access the other group and (3) the platform can facilitate the access more efficiently than bi-lateral relationships between the members of the groups (Evans, 2003). In other words, the benefit enjoyed by a member of one group depends upon how well the platform attracts customers from the other group (Armstrong, 2006).

Hereafter, for expositional convenience, we shall refer to an end-user group who uses an offering of the platform itself, regardless of the presence or absence of any other end-user group, as *attractors* (e.g., readers of news in the case of a newspaper). Also, we shall refer to the end-user group interested in accessing attractors via the platform as *suitors* (e.g. advertisers buying ad-space in the case of a newspaper). The paucity of research on marketing resource allocation and productivity of platform firms is surprising considering that they are pervasive and include many of the most well-known firms in the economy. Table I. 1 lists some renowned platform firms and their attractor and suitor groups.

Table I. 1. Some Examples of Platform firms

Firm Name	Firm Category	Attractor	Suitor
<i>New York Times</i>	Newspaper	Reader	Advertiser
<i>Time Inc.</i>	Magazine	Reader	Advertiser
<i>FOX</i>	Television Station	Viewer	Advertiser
<i>General Growth Properties</i>	Mall Developer	Shopper	Retailer

The peculiar nature of the “two-sided market” of a platform firm has gripped the attention of economists in recent years with a concentration on pricing strategies. For example, Parker and Van Alstyne (2005), Rochet and Tirole (2005), Armstrong and Wright (2004), Jullien (2004) and Bolt and Tieman (2006) examine how standard pricing policies for profit-maximization should be restructured in the presence of two-sidedness while Chakravorti and Roson (2004) and Caillaud and Jullien (2003) study how pricing rules should change in a setting of competing platforms. Roson (2004) provides a detailed review of pricing-related work on two-sided

markets. Some results are that in the presence of CMEs, a) prices applied to the two market sides are both directly proportional to the price elasticity of the corresponding demand (Rochet and Tirole, 2003); b) socially optimal pricing in two-sided markets leads to an inherent cost recovery problem, inducing losses for the monopoly platform (Bolt and Tieman, 2006); and c) in a duopoly, the platform charging the lower fees could potentially capture *both* sides of the market and result in market monopoly (Caillaud and Jullien, 2003).

More recently, a small but growing marketing literature on platform firms has emerged. For example, Chen and Xie (2007) examines the relationship between high levels of attractor loyalty and platform firm profits under competition. Wilbur (2008) estimates a structural model of suitor (advertiser) demand for viewers (attractors) and viewer demand for advertisers in the television industry and finds evidence for ad aversion among viewers. Gupta, Mela and Vidal Sanz (2007) develops a model to calculate the customer lifetime value (CLV) of the buyers (attractors) and sellers (suits) in an auction-house and find that buyer CLV is higher than that of the seller.

This dissertation is aimed at understanding and improving managerial practice in two decision-areas of platform firms- (1) *optimal marketing budgeting* and (2) *benchmarking* on the basis of *efficiency analysis*. There are three reasons for these choices. First, the issues constitute *important* managerial decisions; “*determining the appropriate level of spending and allocation*” of marketing budgets and “*measuring the productivity of the marketing-mix*” are often cited as priority issues by managers (*Institute for the Study of Business Markets Research Priorities*, 2009). Second, the two issues are *not well-understood* by platform managers. Previous research

shows that platform-firm managers are often concerned about where to invest their managerial resources but do not necessarily know how to do so optimally (Rosenthal and Mitchell, 2004). Some media-based platform industries like the newspaper industry are not known to benchmark, e.g. an Inland Press Association Study (2009) finds that “*like many industries, newspapers employ financial “rules of thumb” validated more by continued use than any basis in fact or empirical data*”. Third, most of the scholarly literature to date on marketing budgeting (e.g., Leeflang et al 2000, Hanssens Parsons and Schultz 2001, Mantrala 2002, Gupta and Steenburgh 2008) and benchmarking (e.g. Cooper, Seiford and Tone 2006; Emrouznejad and Thanassoulis 2001) has ignored platform firms; therefore, the special problems of such firms in these areas have remained unresolved.

The empirical setting for this dissertation’s research is the U.S daily newspaper industry. Two reasons motivate the focus on this industry at this time. First, the industry *sorely needs advice* on efficient allocation of resources given they are going through troubling economic times due to tumbling circulations (e.g., Bughin and Poppe 2005). For example, the number of surviving American dailies has dropped from 1772 to 1480 in the last five decades (Picard, 2004). Circulation has gone from a slow loss to steep drops each quarter. A literature search reveals a dearth of econometric model-based decision aids in this area. Second, currently newspaper firms are undergoing a strategic transformation, involving consolidation in some cases and deconsolidation in others as they struggle to retain readers who are migrating to online sources of news and information. In such circumstances, accurate evaluation and benchmarking of the efficiencies of their decision making units is critical.

In sum, this dissertation is designed to answer the overarching research question “How to formulate and employ optimal marketing budgeting/allocation and benchmarking decisions in the platform-firm context?” In addressing this focal research question, this dissertation provides contributions to the marketing literature through two essays. Section I.2 provides a specific summary of the contributions of each essay.

I. 2. Specific Contributions of the Research

Marketing budgeting and planning problems are usually solved by first formulating a *sales-response model* that captures how demand from an entity (product, region or customer group) is influenced by marketing efforts over time. Sales-response models in the platform-firm context must capture the notion that the benefit enjoyed by a member of one group depends upon how well the platform firm attracts members from another group, i.e., the extent of cross-market effects (CMEs). Previous research studied “one-sided” markets where CMEs are absent, thereby providing little guidance for dynamic marketing investment planning by platform firms. Hence, to advance knowledge in this area through Essay 1, we first provide normative analysis using optimal control theory and offers insights into dynamically optimal marketing investments for a platform firm such as a local daily newspaper with two end-user groups. We show how CMEs impact optimal investment levels and allocation ratios, extending and even reversing the extant normative budgeting rules obtained from models that ignore CMEs. For instance, in the presence of certain CME structures, even when marketing, (e.g., sales force efforts) towards one group (advertisers) may be very effective, the portion of the overall budget allocated towards that group

should be reduced rather than increased. Second, we estimate and validate the proposed model empirically to assess the contribution of the estimated CMEs to marketing elasticities.

Specifically, by applying the Kalman Filter method to real market data from a daily print newspaper company, the presence of CMEs is established, i.e., the firm's marketing investments targeted to two separate end-user groups have significant direct and indirect sales effects. Third, we develop a tool that allows a platform manager to set budgets optimally for any planning horizon by taking CMEs into account. Finally, we discuss the implications with respect to the current trend of newsroom staff cutbacks in the industry.

Productivity 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). Essay 2 focuses on the issue of benchmarking DMUs in the *media* industry due to the relevance and importance of such assessments today. The media-firm's two-sided business model presents three challenges that an appropriate benchmarking approach must take into account. Specifically,

- 1) It should provide efficiency scores at the department-level (rather than the aggregate level) since departments of a media-platform serve different consumer groups and the very sustenance of any two-sided platform is tied to how well it can retain *both* consumer groups.
- 2) It must recognize that some department outputs in a media-platform are *mutually inter-linked*, i.e. two department's outputs could serve as mutual inputs to each other.

- 3) It should acknowledge the role of error. Specifically, the approach should allow us to *estimate* (rather than simply calculate) and statistically test (rather than assume) the impact of increase in departmental efficiency on the firm's outputs.

No single prevalent method in the literature handles *all the three challenges* noted above. In Essay 2 our first contribution is to fill this need. Specifically, we combine the relatively new techniques of *Network DEA* (NDEA) and *Multivariate Sliced Inverse Regression* (MSIR) and adapt them in a fashion that tackles all three challenges mentioned above. Our proposed approach is fairly general and can also be used in benchmarking other (non-media) two-sided platforms (e.g. shopping malls). The second contribution is empirical demonstration/validation of the approach. Using unique syndicated source data on U.S. print newspaper firms, we demonstrate how the proposed approach outperforms applications of the existing approaches applied to platform-firms. We also derive substantive insights useful to the newspaper industry.

In summary, the two essays advance extant knowledge and methods with respect to solving marketing budgeting and benchmarking problems of platform-firms as well as highlighting the nuances that distinguish these from “classic” firms.

I. 3. Organization of the Dissertation

The remainder of this dissertation is organized into two chapters. The second chapter is titled “*Dynamic Marketing Investment Strategies for Platform Firms*” and deals with the marketing budgeting problem of a platform firm. The third chapter titled “*Benchmarking Media-Platforms: A Method and Application to Daily Newspapers*” deals with the issue of media-based platform

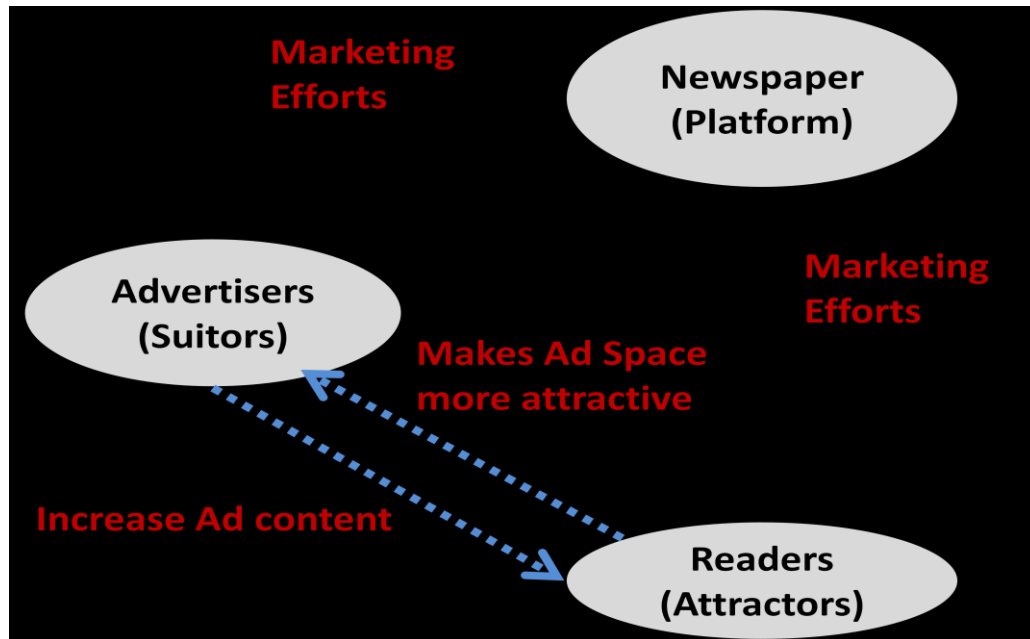
benchmarking. The references and an appendix including mathematical derivations are attached at the end of this document.

CHAPTER II: DYNAMIC MARKETING INVESTMENT STRATEGIES FOR PLATFORM FIRMS

Deciding the optimal levels and allocation of scarce marketing resources is a fundamental responsibility of marketing managers. Not surprisingly, a large volume of work in the marketing models literature has focused on developing normative rules for marketing resource allocation decisions, empirical analyses of the optimality of firms' marketing investments in practice, and building implementable model-based tools for optimizing marketing investment decisions in specific settings (Mantrala, 2002). However, surveys of this literature (e.g., Leeflang et al 2000, Hanssens Parsons and Schultz 2001, Mantrala 2002, Gupta and Steenburgh 2008) reveal that most of the research to date has ignored marketing budgeting and allocation decisions by a pervasive and important class of firms in the economy, namely, *platform* firms that do business in *'two-sided'* markets.

The key feature of platform-firm markets, distinguishing them from the 'one-sided' classic firm markets treated in much of the previous literature, is that they have two or more different groups of customers (end-users of their products or service offerings) that businesses have to get and keep on board to succeed (Rochet and Tirole, 2005). In other words, the benefit enjoyed by a member of one group depends upon how well the platform attracts customers from the other group (Armstrong, 2006) and, thus, two-sided markets are characterized by dynamic "cross-market effects" (CMEs), e.g., Chen and Xie (2007). Figure 1 provides a diagrammatic representation of a newspaper firm allocating marketing efforts to its attractor and suitor groups.

Figure I.1: Newspaper Allocating Marketing Efforts



The newspaper invests in marketing to increase its readership or circulation (e.g., enhancing news content quality). However, its suitors (advertisers) are specifically interested in the number and composition of the newspaper’s attractors (readers) who they want to reach. Therefore, the newspaper firm invests in communicating this information to the suitors (e.g., by employing a sales force to sell ad-space). The resultant suitors’ interest in and use of the newspaper in turn can impact future demand for the newspaper from its attractors. Specifically, an increase in the quantity of advertising in the newspaper can potentially increase/decrease demand from the attractors. Thus, these two sources of revenue for the newspaper are interrelated (Dewenter, 2003).

The paucity of research on optimal marketing resource allocation by platform firms is surprising considering that many are among the largest in the economy, including a number of Fortune 100 companies like Time Inc (magazine) and FOX (television network); make significant marketing investments; and are concerned about the effectiveness of these investments (Rosentiel and Mitchell, 2004). From a modeling viewpoint, two novel and challenging aspects for platform firms' marketing budgeting are as follows. First, these decisions must account for the differential dynamic (carryover) effects of marketing on the demands from the dual or multiple sides of the platform firm's business. Second, they must take into account the CMEs of marketing efforts towards the multiple end-user groups. These challenges are noted, for example, by Evans and Schmalensee (2007): "*... its [platform's] customer groups form a dynamic system and live in a non-linear world ... Changes in customers of one type affect customers[readers, advertisers] of the other type ...*" and that a newspaper firm "*... must consider the interdependence of these two groups of customers [readers, advertisers] at every turn ...*" Therefore, the objectives in this chapter are three-fold:

1. Extend extant marketing budgeting theory by deriving normative rules for platform firms (Section II.3 -II.5);
2. Estimate and validate empirically a proposed two-sided response model using market data from an archetypal platform firm, namely a daily print newspaper company, and gain insights into the signs and magnitudes of dynamic CMEs and their impact on marketing elasticities (Section II.6).

3. Develop and demonstrate the use of a model-based decision-making tool for improving dynamic planning by marketing managers of the daily newspaper firm who collaborated with us in this research (Section II.7).

The research yields the following results and findings. Section II.4 and II.5 present five new propositions that show how dynamic CMEs together with carryover effects result in different optimal marketing-investment levels and allocations in platform firms compared to classic firms (without CMEs). Also, the results indicate that optimal investment levels could be set higher or lower than those of classic firms depending on whether CMEs reflect *reinforcing* effects (CMEs in both directions are positive) or *counteractive* effects (when the CME in one direction is positive while the CME in the other direction is negative). Further, some rule reversals from the classic setting are highlighted, e.g., in the presence of certain CME structures, even when marketing efforts towards one group (e.g. advertisers) may be very effective, the portion of the overall budget allocated towards that group should be reduced rather than increased. .

In Section II. 6, using data from a local newspaper firm, a two-sided sales response model is specified and calibrated via state-space methods (e.g. Xie et al 1997; Naik, Mantrala and Sawyer, 1998). Three important findings emerge from this empirical analysis. First, these market data furnish empirical support for the proposed response model, i.e., a model that includes CMEs performs better than the one without CMEs. Second, the attraction effect and the suitor effect are both significant and positive, revealing that this particular newspaper is a reinforcing platform. A positive suitor effect indicates that the newspaper's readers value advertising, unlike T.V. viewers who were found to be ad-averse by Wilbur (2008). Third, the significant CMEs

imply marketing efforts have both direct and indirect effects, i.e., efforts towards one end-user group also influence the other end-user group. In the context of the newspaper, the overall (direct + indirect) elasticity of investment in the newsroom or improving product (news) quality to attract readers is 50% greater than the overall elasticity of investments in marketing, i.e., sales force effort, directed at advertisers.

In II.7, a model-based decision-making tool is developed that provides the optimal investment-mix that maximizes profits over a manager's preferred planning horizon. The managers can evaluate the resulting optimal investment levels by using parameter estimates of the calibrated model based on market sales and investment data. Using a hold-out sample from the newspaper firm, we find that that the firm was investing in a sub-optimal fashion --- it was under-spending in the newsroom and over-spending on the sales force. Additionally, the profits obtained from their sub-optimal policy could be improved by using this decision-making tool. Specifically, the optimal marketing-investment policy yields a projected 10% profit increase in the hold-out period. The next section reviews the extant literature to highlight the open questions addressed by our research. .

II. 1. Relevant Literature on Marketing Budgeting

Previous work on multi-region and multi-product marketing budgeting models appears to be related to this study, but those models did not incorporate CMEs. Specifically, Ingene and Parry (1995), Urban (1975a, 1975b), and Gensch and Welam (1990) examine the issues of how managers should allocate their marketing budget between multiple regions when marketing effort in one region impacts sales in another region. Similarly, Gijsbrechts and Naert (1984),

Doyle and Saunders (1990) and Reibstein and Gatignon (1984) examine the issues of how managers in charge of selling multiple products should set their marketing budgets optimally taking into account complementary and substitution effects. Both multi-region and multi-product models incorporate marketing spillover effects, but do not consider explicit demand interdependence. That is, these extant models incorporate spillover effects from one region or product to another region(s) or product(s) bought by the same end-user group, whereas CMEs capture demand interdependence between two different end-user groups.

More recently, a small but growing marketing literature on platform firms has emerged. For example, Chen and Xie (2007) examine the relationship between high levels of attractor loyalty and platform firm profits under competition. Wilbur (2008) estimates a structural model of suitor (advertiser) demand for viewers (attractors) and viewer demand for advertisers in the television industry and finds evidence for ad aversion among viewers. Gupta, Mela and Vidal Sanz (2007) develops a model to calculate the customer lifetime value (CLV) of the buyers (attractors) and sellers (suitsors) in an auction-house and find that buyer CLV is higher than that of the seller. Mantrala, Naik, Sridhar and Thorson (MNST) 2007 address the newspaper marketing budgeting allocation problem using a static model and empirically assess the optimality of short-term expenditures of a cross-section of firms in the newspaper industry. In contrast, this study focuses on marketing optimization over the long-term by one firm, incorporating the dynamic effects of both CMEs and sales carryover. To this end, we specify a sales response function, formulate the budget allocation problem, and derive both general and

specific insights into dynamically optimal marketing investments towards attractors and suitors in reinforcing and counteractive markets.

II. 2. Sales Response Function

We consider a monopolist platform firm such as a local daily newspaper (98% of daily newspapers are the only ones published in their market (Picard, 1993)). In addition, we assume that margins from both the attractor and suitor groups are constant because (i) newspaper retail prices are observed to stay fixed over four to seven years (Bils and Knelow, 2002) and variable costs (e.g. newsprint costs) are constant after the first-copy costs (MNST 2007, p. 29), and (ii) advertising rates for local newspapers, once published, are not negotiable and remain unchanged for long periods of time (Warner and Buchman, 1991, p 205).

Let A_t and S_t denote the dollar sales revenues at time t from the attractor and suitor sides of the market, respectively. Then we specify the platform's dynamic sales- marketing effort response system as follows:

$$\begin{bmatrix} A_t \\ S_t \end{bmatrix} = \begin{bmatrix} \lambda & \theta_a \\ \theta_s & \lambda \end{bmatrix} \begin{bmatrix} A_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} f(u_t) \\ g(v_t) \end{bmatrix} \quad (1)$$

In equations (1), u_t and v_t denote marketing efforts allocated towards attractors and suitors respectively, while $f(\cdot)$ and $g(\cdot)$ denote the corresponding response functions, which are assumed to be concave to capture diminishing returns to marketing efforts such as investments in product quality (Rust, Zahorik and Keiningham 1995) or marketing communications (e.g., Simon and Arndt 1980; Mantrala, Sinha, and Zoltners 1992). The sales realized in period t are then the sum of sales generated by current period efforts and fractions of previous period's sales

that are carried over to the current period. In Equation (1), λ_A and λ_S denote these carryover fractions of attractor sales and suitor sales, respectively.

Next, we define the dynamic cross-market effects (CMEs) that constitute the novel features of platform (two-sided) markets. Specifically, in Equation (1), θ_{AS} denotes an *attraction effect* coefficient that captures the dynamic effect of increased attractor demand in period $t-1$ on suitors' demand in period t . We expect θ_{AS} to be positive because suitors seek access to attractors and their demand for the medium of the platform should increase when they observe a higher level of attractors' demand for the platform. Similarly, θ_{SA} denotes *suitor-repercussion effect*, which can be positive or negative depending on whether attractors value suitors' use of the platform, e.g. newspaper readers may be “ad-lovers” (Sonnac, 2000) or T.V. viewers may be “ad-averse” (Wilbur, 2008). Together, we refer to the platform market setting as *reinforcing* when $\theta_{AS} > 0$ and $\theta_{SA} > 0$, and as *counteractive* when $\theta_{AS} > 0$ and $\theta_{SA} < 0$. To determine how much should the platform-manager spend on marketing efforts, we next analyze the continuous-time form of the sales response system (1).

II. 3. Marketing Decision Problem Formulation and General Solution

Let $u(t)$ and $v(t)$ denote the marketing investments towards attractors and suitors, respectively. We assume the platform firm's goal is to maximize discounted long-term profits and, therefore, its problem is expressed as

$$\text{Maximize } J(u, v) = \int_0^{\infty} e^{-\rho t} \pi(A(t), S(t), u(t), v(t)) dt, \quad (2)$$

$$\text{where } \pi(A, S, u, v) = n_A A + n_S S - c_A u - c_S v, \quad (3)$$

and m_A and m_S represent the margins on unit sales to attractors and suitors, respectively. In determining the optimal effort levels, denoted u^* and v^* , the manager needs to account for CMEs and the dynamics of market response. Denoting $\dot{x} = dx(t)/dt$, we express equation (1) in continuous-time as

$$\begin{bmatrix} \dot{A} \\ \dot{S} \end{bmatrix} = \begin{bmatrix} -(1-\nu_A) & \theta_{SA} \\ \theta_{AS} & -(1-\nu_S) \end{bmatrix} \begin{bmatrix} A \\ S \end{bmatrix} + \begin{bmatrix} f(u) \\ g(v) \end{bmatrix} \quad (4)$$

and solve the maximization problem defined by (2)-(4) by applying optimal control theory (see, e.g., Kamien and Schwarz 1992, or Sethi and Thompson 2006). To this end, we first define the current-value Hamiltonian

$$H = n_A A + n_S S - \rho + \mu_1 [-(1-\lambda_A)A + \theta_{SA}S + f(u)] + \mu_2 [-(1-\lambda_S)S + \theta_{AS}A + g(v)] \quad (5)$$

where μ_1 and μ_2 represent the co-state variables corresponding to \dot{A} and \dot{S} , respectively. By applying the Pontryagin's maximum principle, we obtain the first-order conditions:

$$\frac{\partial H}{\partial u} = 0 \Rightarrow \mu_1 \frac{\partial f}{\partial u} = 0 \quad (6)$$

$$\frac{\partial H}{\partial v} = 0 \Rightarrow \mu_2 \frac{\partial g}{\partial v} = 0 \quad (7)$$

and

$$\dot{\mu}_1 = \rho \mu_1 - \frac{\partial H}{\partial A} = \rho \mu_1 - n_A + \lambda_1(1-\lambda_A) - \lambda_2 \theta_{AS} \quad (8)$$

$$\dot{\mu}_2 = \rho \mu_2 - \frac{\partial H}{\partial S} = \rho \mu_2 - n_S + \lambda_2(1-\lambda_S) - \lambda_1 \theta_{SA} \quad (9)$$

Next, using the transversality conditions (Kamien and Schwartz 1992, p.175), we obtain the stationary μ_{-} and μ_{+} given below:

$$\begin{bmatrix} \mu_{+} \\ \mu_{-} \end{bmatrix} = \frac{1}{[(\rho + 1 - \lambda_{-})(\rho + 1 - \lambda_{+}) - \theta_{-S}\theta_{-A}]} \begin{bmatrix} m_A(\rho + 1 - \lambda_{-}) + m_S\theta_{-S} \\ m_A\theta_{-A} + m_S(\rho + 1 - \lambda_{+}) \end{bmatrix} \quad (10)$$

Finally, we substitute μ_{+} and μ_{-} from (10) into (6) and (7) to obtain the gradient condition,

$$\begin{bmatrix} \left. \frac{\partial f}{\partial u} \right|_{u=u^*} \\ \left. \frac{\partial g}{\partial v} \right|_{v=v^*} \end{bmatrix} = \begin{bmatrix} \frac{(\rho + 1 - \lambda_{-})(\rho + 1 - \lambda_{+}) - \theta_{-S}\theta_{-A}}{m_A(\rho + 1 - \lambda_{-}) + m_S\theta_{-S}} \\ \frac{(\rho + 1 - \lambda_{-})(\rho + 1 - \lambda_{+}) - \theta_{-S}\theta_{-A}}{m_A\theta_{-A} + m_S(\rho + 1 - \lambda_{+})} \end{bmatrix} \quad (11)$$

This gradient condition can be applied to obtain exact solutions for u^* and v^* upon specifying the sales response functions f and g . For instance, let us suppose they have the square-root form as in Naik and Raman (2003), i.e., $f(u) = \beta \sqrt{u}$ and $g(v) = \beta \sqrt{v}$. Then the gradient condition in (11) becomes:

$$\begin{bmatrix} \sqrt{u^*} \\ \sqrt{v^*} \end{bmatrix} = \frac{1}{2[(\rho + 1 - \lambda_{-})(\rho + 1 - \lambda_{+}) - \theta_{-S}\theta_{-A}]} \begin{bmatrix} \beta [m_A(\rho + 1 - \lambda_{-}) + m_S\theta_{-S}] \\ \beta [m_A\theta_{-A} + m_S(\rho + 1 - \lambda_{+})] \end{bmatrix} \quad (12)$$

We can now see that previous solutions for optimal investment levels in classic firms are special cases of (12). Specifically, we can obtain the static Dorfman and Steiner (1954) result by setting the carryover parameter values $\lambda_S = \lambda_A = 0$ (No Dynamics) and $\theta_{AS} = \theta_{SA} = 0$ (No CMEs). That is,

$$\begin{bmatrix} u^* \\ v^* \end{bmatrix} = \frac{1}{4} \begin{bmatrix} (\beta n_A)^2 \\ (\beta n_S)^2 \end{bmatrix} \quad (13)$$

Similarly, we can obtain the dynamic Nerlove-Arrow (1962) result from (12) by setting $\theta_{AS} = \theta_{SA} = 0$ (No CMEs). That is,

$$\begin{bmatrix} u^* \\ v^* \end{bmatrix} = \begin{bmatrix} \frac{(\beta n_A)^2}{4(\rho + 1 - \lambda_+)^2} \\ \frac{(\beta n_S)^2}{4(\rho + 1 - \lambda_-)^2} \end{bmatrix} \quad (14)$$

Comparing (13) and (14), we learn that the optimal spending levels (u^*, v^*) in (14) are larger than those in (13) as a result of accounting for sales dynamics. Intuitively, marketing spending levels should be increased to take advantage of the carryover effects (λ_A, λ_S) when they are present (e.g., Sinha and Zoltners 2001). Next, reverting to the optimality conditions (11), we derive several general insights into how CMEs affect optimal investment levels in different types of platforms.

II. 4. General Results on Optimal Investment Levels in Platform Firms

Applying the gradient condition in (11), we compare the optimal investment levels in two types of platforms against a benchmark classic firm with the same sales carryover dynamics and discount rate but no CMEs ($\theta_{SA} = \theta_{AS} = 0$) and obtain the following result:

Result 1. Optimal marketing efforts by reinforcing platform firms (θ_{AS} and $\theta_{SA} > 0$) directed at both attractors and suitors are greater than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$).

Proof. The gradient condition (11) reveals that $df/du|_{u^*}$ for reinforcing platforms is less

than $df/du|_{u=^*}$ for classic firms. Furthermore, for any concave function f ,

$df/du|_{u_1^*} < df/du|_{u_2^*}$ implies $u_1^* > u_2^*$, thus proving the claim for attractors.

Similarly, $dg/dv|_{v=^*}$ for reinforcing platform is less than $dg/dv|_{v=^*}$ for classic firms, indicating that suitors v^* (reinforcing platform) $>$ v^* (classic firms).

An example of a reinforcing platform is a local newspaper with ad-loving readers (e.g., Sonnac 2000). Result 1 offers the insight that when CMEs are mutually reinforcing, a profit-maximizing platform firm's marketing spending should be *more not less* than that of its counterpart classic firm as intuition might suggest.

Result 2. Optimal marketing efforts by counteractive platforms ($\theta_{AS} > 0$, $\theta_{SA} < 0$) directed at attractors are greater than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$) provided the margin ratio m_S/m_A exceeds a critical value, m^ .*

Proof. The gradient condition (11) reveals that $df/du|_{u=^*}$ for counteractive platforms is less than $df/du|_{u=^*}$ for classic firms when $m_S(\rho + 1 - \lambda) + \theta_{SA}m_A > 0 \Rightarrow m_S/m_A > m^*$, where the critical value $m^* = \frac{|\theta_{SA}|}{\rho + 1 - \lambda}$ and $|x|$ denotes the absolute value of x .

Furthermore, $df/du|_{u_1^*} < df/du|_{u_2^*}$ implies $u_1^* > u_2^*$, indicating that u^* (counteractive platform) $>$ u^* (classic firm) when $m_S/m_A > m^*$, as posited.

This result reveals an important managerial trade-off is required in counteractive platforms. Increasing marketing towards attractors (u) leads to an increase in attractor revenue (A) and subsequently, an increase in suitor revenue (S) through the attraction effect (θ_{AS}). However, an increase in suitors and, therefore, in suitor revenues deters the long-term revenue from attractors, e.g., in a setting with ad-avoiding newspaper and magazine readers (Sonnac, 2002). The amount of loss depends on the magnitude of the negative suitor-effect θ_{SA} and the long-term purchase reinforcement effect of attractors (λ_A). The critical point m^* , given by $|\theta_{SA}|/(\rho + 1 - \lambda)$, is the margin ratio m_S/m_A at which the long-term profit contribution of the suitor revenue exceeds the lost contribution due to lower attractor revenues. The critical margin ratio increases as the suitor-effect or the carryover effect increases, and it decreases with the discount rate.

Result 2 suggests that rather than indiscriminately adding attractors, managers of counteractive platforms should tailor their marketing messages to gain attractors who may be more tolerant to suitors. For example, past research reveals significant ad-avoidance heterogeneity among the potential readers of magazines and newspapers (Sonnac 2002; p 251). In such situations, managers may find it useful to target market segments that are less ad-avoiding.

Result 3. Optimal marketing efforts by counteractive platforms ($\theta_{AS} > 0$, $\theta_{SA} < 0$) directed at suitors are smaller than those by classic firms ($\theta_{AS} = \theta_{SA} = 0$).

Proof. From the gradient condition in (11), $dg/dv|_{v=^*}$ for a counteractive platform is greater than $dg/dv|_{v=^*}$ for classic firms. Furthermore, $dg/dv|_{v_1^*} > dg/dv|_{v_2^*}$ implies

$v_1^* < v_2^*$, indicating that v^* (counteractive platform) $<$ v^* (classic firm), which proves the claim.

Result 3 reveals that marketing investment toward the suitors (v^*) should be lower in counteractive platforms, i.e., although the effect of v in increasing the number of suitors may be large, the negative value of θ_{SA} reduces its overall long-term effectiveness, which reduces its optimal spending level. Result 3 has implications for investments in ad-selling effort of platforms like radio broadcasters. News radio stations commonly employ salespeople to sell *piggyback* slots to retailers, i.e., multiple slots that are scheduled back-to-back. While these significantly increase revenue for the station, they increase the units of ads heard during a program and increase the clutter of messages (Warner and Buchman, 1991, pg 229). Increased clutter may contribute to wasted coverage (i.e., listeners not buying from the advertisers) or even lead to a high turnover (i.e., listeners switching stations). Increasing investment in the sales force may not be optimal for the station as a whole in such situations, even if the sales force is effective in selling piggyback slots to retailers.

II. 5. Moderating Role of ‘Other Market’ Sales Carryovers

In the absence of CMEs ($\theta_{AS} = \theta_{SA} = 0$), it can be shown that a firm’s optimal marketing effort level towards one end-user group is unaffected by the magnitude of the sales carryover factor in the second end-user group or “other-market”. In contrast, other-market sales carryover

does influence the optimal level of marketing investment in the first group when CMEs are present. We characterize the nature of this influence in the following two results.

Result 4. Optimal marketing efforts towards attractors increase as (a) λ_S increases in reinforcing platforms and (b) λ_S increases in counteractive platforms provided m_S/m_A exceeds the critical value m^ .*

Proof. A decrease in $df/du|_{u=u^*}$ implies an increase in u^* . Furthermore, the change in

$$df/du|_{u=u^*} \text{ with respect to } \lambda_S \text{ is given by } \frac{\partial^2 f}{\partial u \partial \lambda} \Big|_{u=u^*} = \frac{-\lambda_S [m_S(\rho + 1 - \lambda_S) + \theta_{SA} m_A]}{n_A(\rho + 1 - \lambda_S) + n_S \theta_{SA}^2},$$

which is negative in reinforcing platforms because $\theta_{SA} > 0$ and $\theta_{AS} > 0$.

Consequently, u^* in reinforcing platforms increases with λ_S . Additionally,

$$\frac{\partial f}{\partial \lambda} \Big|_{u=u^*} \text{ is negative in counteractive platforms } (\theta_{AS} > 0, \theta_{SA} < 0) \text{ when}$$

$m_S(\rho + 1 - \lambda_S) + \theta_{SA} m_A > 0 \Rightarrow m_S/m_A$ exceeds m^* , the critical margin ratio. This completes the proof.

This result has direct implications for media-selling strategies. For example, many retailers who advertise in print news platforms (newspapers, magazines) plan their calendars for extended periods of time and rely on “past media usage” patterns while placing recurring ads in a platform

(Warner and Buchman, p 258-259). From the platform's perspective, this situation represents a setting with high sales carryover (λ_S) due to purchase reinforcement effects from its suitors (advertisers). To be able to procure ads from the retailers, the platform should increase its marketing spending to its attractors since a large attractor base is valued by retailers who stay with the same platform for longer periods of time. In counteractive platforms, the platform should only increase its marketing towards attractors after ensuring that its margin ratio m_S/m_A exceeds m^* as per the logic in Result 2.

Result 5. Optimal marketing efforts towards suitors (a) increases as λ_A increases in reinforcing platforms and (b) decreases as λ_A increases in counteractive platforms (regardless of the margin ratio).

Proof. A decrease in $dg/dv|_{v=v^*}$ implies an increase in v^* . Furthermore, the change in

$$dg/dv|_{v=v^*} \text{ with respect to } \lambda_A \text{ is given by } \frac{\partial g}{\partial \lambda_A} = \frac{-\lambda_A[m_A(\rho + \dots) + \lambda_S m_S]}{[n_S(\rho + \dots) + n_A \theta_{SA}^2]},$$

which is negative in reinforcing platforms ($\theta_{SA} > 0, \theta_{AS} > 0$). This implies a reduction

$dg/dv|_{v=v^*}$ and thus an increase in v^* in reinforcing platforms as λ_A increases.
in

Additionally, $\frac{\partial^2 g}{\partial \lambda_A^2}$ is positive in counteractive platforms because $\theta_{AS} > 0$ and $\theta_{SA} <$

0, implying v^* increases as λ_A increases. This completes the proof.

Result 5 implies *opposite* investment policies towards the suitors in reinforcing and counteractive platforms. Specifically, a high value of λ_A represents high purchase reinforcement effects on the attractor side of the platform, e.g., renewed subscriptions to magazines or pay-per-view channels. In a situation where attractors with higher long-term revenue potential actually like suitor presence, marketing efforts towards suitors should be increased. However, marketing efforts towards suitors should be decreased when attractors avoid suitors because then increasing suitor presence leads to loss of attractors with long-term revenue potential as well as subsequent loss in suitor revenue due to loss of attractors.

In sum, Results 1 through 5 highlight the fact that optimal budgeting rules not only differ for platform firms relative to classical one-sided markets, but also vary across different kinds of platform firms (e.g., reinforcing or counteractive). Because different investment strategies hold for different platform firms, managers should estimate parameters of the market response functions to determine whether their platform is reinforcing or counteractive. In the next section, we describe an econometric estimation approach to estimate the proposed two-sided market response model using data from a daily newspaper firm.

II. 6. Empirical Analysis

This section illustrates how managers can establish whether their firm is a reinforcing or counteractive platform by estimating CMEs. To this end, we first describe the data, then the Kalman filter estimation approach, followed by model selection and diagnostics, and finally present the empirical results.

II. 6.1. Data

We obtained data from a privately-held media company that has diversified holdings in newspaper and magazine publishing as well as radio broadcasting. The company wishes to remain anonymous. Medium-sized newspapers (subscriptions < 85000) form the core business of the company, and the particular print newspaper we analyze is a monopolist in its city-region, producing somewhat differentiated news content overall due to its local flavor. A third-party audit bureau verifies this newspaper's subscription figures, and it also provides demographic information (age, gender, income, home ownership) about the newspaper's readers (attractors) to its advertisers (suitsors) who wish to purchase ad space in the future. The newspaper appeals mainly to advertisers who seek to reach audiences older than 50, and these advertisers include financial companies and assisted living centers. Because the newspaper invests heavily in marketing to these advertisers, its share of local advertisers' print advertising budgets is quite high.

The dataset spans the decade January 1997 through December 2006 and contains information on revenues from attractors (readers) and suitsors (advertisers). In addition, the monthly marketing efforts towards these two revenue sources, namely, dollar spending on newsroom and ad-space sales force are provided. Prior work in the journalism literature suggests that investments in the newsroom are akin to investments in product quality (Litman and Bridges, 1986) as the newsroom department is responsible for providing accurate and engaging news stories to its diverse local readers. The field sales force's main task is to provide recent figures on the size and composition of the attractor base to the suitsors as well as inform them

about the potential benefits of purchasing ad-space in certain sections of the newspaper that their targeted attractors might read.

Table II. 2 shows that the company spends about equally in the newsroom (49% of budget) and on the sales force (51% of budget). As is typical in the mature daily newspaper business, subscription and ad-space prices changed only a few times over the 10 year time-span of the data. Margins on sales were high (mean = 0.45) but very stable (standard deviation = 0.03) during this 10-year period. To calibrate the model using these data, we next describe an approach for estimation, inference and model selection.

Table II. 2. Firm Descriptive Statistics

Variables*	Means	Std. Deviations
Attractor Revenues (Subscription)	60.04	4.43
Suitor Revenues (Advertising)	202.4	19.45
Newsroom Department Investments	22.14	1.30
Salesforce Department Investments	21.02	2.56

* All variables in 10, 000 U.S. dollars per month.

II. 6.2. Kalman Filter Estimation

Equation 1 represents a system of stochastic difference equations with non-linear decision variables, inter-temporal dependence of demand, and potentially correlated error structures. Because ordinary least squares approach can yield biased estimates when estimating dynamic models (Naik, Schultz, and Srinivasan, 2006), we apply state-space methods (e.g.

Harvey, 1994). Specifically, we use a multivariate Kalman Filter (KF) to estimate equation (1) via the following three steps:

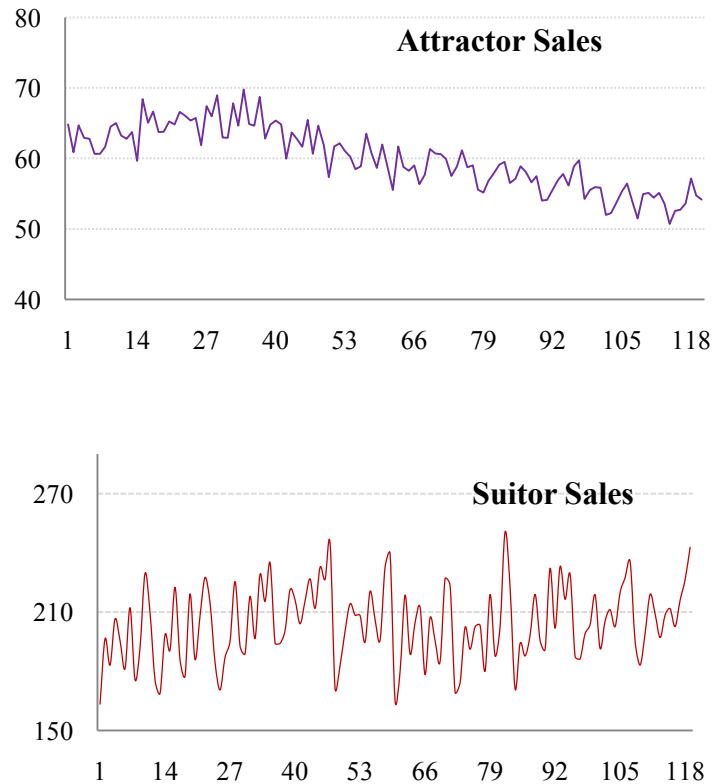
Step 1 Transition Equation: The transition equation specifies the model dynamics and captures the influence of marketing efforts. We obtain the transition equation by allowing the de-seasonalized attractor and suitor revenues to be influenced by their own past values through carryover effects (λ_A, λ_S) as well each other's past sales values through CMEs (θ_{AS} and θ_{SA}). In addition, we allow the revenues to be influenced by marketing efforts; specifically, we chose square-root functional forms based on their simplicity and popularity in the marketing-sales response literature (e.g., see Naik, Prasad and Sethi, 2008 for a recent application). The transition equation is thus specified as

$$\begin{bmatrix} A_t \\ S_t \end{bmatrix} = \begin{bmatrix} \lambda & \theta_S \\ \theta_A & \lambda \end{bmatrix} \begin{bmatrix} A_{t-1} \\ S_{t-1} \end{bmatrix} + \begin{bmatrix} \beta \sqrt{u_t} \\ \beta \sqrt{v_t} \end{bmatrix} + \begin{bmatrix} \omega_{A,t} \\ \omega_{S,t} \end{bmatrix} \quad (15)$$

where A_t and S_t represent the attractor and suitor revenue; u_t and v_t represent the investments towards the attractors and suitors respectively; β_A and β_S represent marketing effectiveness parameters of u and v , respectively; and $\omega = (\omega_{A,t}, \omega_{S,t})'$ is the transition error vector that follows $N(0, Q)$, where Q is the 2 x 2 covariance matrix.

Step 2 Observation Equation: We link the transition equation to the observation equation, which includes factors like trends and seasonality. Figure 2 displays the actual sales observations over time. Attractor sales exhibit a general downward trend, reflecting the general decline in print newspaper readership due to the growth of online newspapers in the U.S.

Figure I.2: Observed Attractor and Suitor Sales Patterns



To account for this decline, we construct a time-trend variable. Additionally, to capture the role of the Internet in this general decline of print newspaper readership, we obtain annual ad revenues of online newspapers from the State of the News Media database (www.stateofthenewsmedia.org) and interpolate it to get monthly online ad revenues via the Biyalogorsky and Naik (2003) approach, which is based on the theory of cubic splines. We also construct two dummy variables to account for seasonality in the suitor revenue (see Figure 4), i.e., a rise in the year-end Christmas season and a dip in the beginning of the year. Thus, the observation equation is given as

$$\begin{bmatrix} Y_{At} \\ Y_{St} \end{bmatrix} = \begin{bmatrix} A_t \\ S_t \end{bmatrix} + \begin{bmatrix} \gamma_1 t + \gamma_2 OAD_t \\ \gamma_3 D_{1t} + \gamma_4 D_{2t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \quad (16)$$

where Y_{At} and Y_{St} represent the actual observed values of attractor and suitor revenues, OAD represents the total ad revenue of online newspapers in the US, γ_1 and γ_2 capture the trend and online ad-revenue effects on Y_{At} , while γ_3 and γ_4 control for the seasonal year-end and beginning effects via the dummy variables D_{1t} and D_{2t} defined as follows:

$$D_{1t} = \begin{cases} 1 & \text{if } t = (11,12), (23,24), \dots, (119,120) \text{ for } t \in (1,120) \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

$$D_{2t} = \begin{cases} 1 & \text{if } t = (1,2), (13,14), \dots, (109,110) \text{ for } t \in (1,120) \\ 0 & \text{otherwise} \end{cases} \quad (18)$$

Finally, the observation error vector $\varepsilon = (\varepsilon_1, \varepsilon_2)'$ follows $N(0, H)$, where H represents a 2×2 diagonal matrix for observation variances.

Step 3- Likelihood Function: Using the KF recursions (Harvey 1994, p. 88) and denoting Y_t as $(Y_{At}, Y_{St})'$, we compute the log-likelihood function,

$$LL(\Psi | Y_T) = \sum_{t=1}^T Ln(p(Y_t | \mathfrak{F}_t)) \quad (19)$$

where $p(\cdot)$ denotes the conditional density of Y_t given the history of information up to the previous period \mathfrak{F}_t . The parameter vector Ψ contains the model parameters

$(\lambda_1, \lambda_2, \theta_1, \theta_2, \beta_1, \beta_2, \gamma_1, \gamma_2, \gamma_3, \gamma_4)'$ together with the observation and transition covariance matrices and the initial means $(A_0, S_0)'$. By maximizing the likelihood function in (19), we obtain the maximum-likelihood estimates:

$$\Psi = \underset{\Psi}{\text{ArgMax}} LL(\Psi | Y_T) \quad (20)$$

To determine significance levels and conduct statistical inference, we obtain the standard errors of the estimated parameters from the square roots of the diagonals of the inverse of the information matrix

$$\hat{I} = \left[- \frac{\partial^2 LL(\Psi)}{\partial \theta \partial \theta'} \right]_{\theta = \hat{\theta}} \quad (21)$$

which is evaluated at the estimated parameter values.

II. 6.3. Model Selection and Diagnostics

Model Selection: To compare various models by balancing fidelity and parsimony, we use the three information criteria: Akaike Information Criteria (AIC), Bias-corrected AIC (AIC_c), and Bayesian Information Criteria (BIC). First, we compare models with and without correlated errors terms in the attractor and suitor transition and observation equations. Table II. 3 shows that the best model --- the one that attains the lowest values on information criteria --- has correlated observation noise, but uncorrelated transition noise. Second, we compare models with and without CMEs.

Table II. 3: Best Error Structure

Models	Transition Noise Covariance	Observation Noise Covariance	AIC	AICc	BIC
1	No	No	1044.94	1050.94	1087.54
2	No	Yes	1026.97	1033.74	1072.35
3	Yes	No	1042.91	1049.68	1088.29
4	Yes	Yes	1028.41	1036.01	1076.58

Table II. 4 indicates that the model with CMEs performs the best. Thus, based on all three criteria, market data lend support to the presence of CMEs. Next, we test for exogeneity of marketing investments.

Table II. 4: Presence of CMEs

Models	CMEs Included?	AIC	AICc	BIC
1	No	1033.78	1039.06	1073.59
2	Yes	1026.97	1033.74	1072.35

Exogeneity of Marketing Investments: Applying the approach developed by Engle, Hendry and Richard (1983), we test for exogeneity of newsroom and salesforce investments. Let $p_1(A, u)$ be the joint density of attractor revenues and newsroom investments; $p_2(A|u)$ denote the conditional density of attractor revenues given newsroom investments; and $p_3(u)$ represent the marginal density. Then we factorize $p_1(A, u) = p_2(A|u) \times p_3(u)$, and weak-exogeneity means that a precise specification of $p_3(\cdot)$ is not needed and no loss of information occurs when we proceed with estimation using the condition density $p_2(\cdot)$. Engle et al (1983) develop a test for exogeneity, which we applied and found support that newsroom and sales force investments are weakly exogenous. If this test were to reject exogeneity, then we would apply instrumental variables method to control for the presence of endogeneity.

Predictive Accuracy: We conduct a cross-validation study to assess predictive accuracy. Specifically, we estimate our model using 96 observations and forecast the remaining 24 observations in the hold-out sample using the estimates from the calibrated model. Numerical

metrics indicate reasonable predictive accuracy. Specifically, the mean absolute deviation of the attractor revenues was 4% and that of suitor revenues was 8%, both suggesting a small deviance from the actually observed values in the hold-out sample.

In sum, these diagnostic tests furnish evidence that the proposed model not only is a parsimonious specification, but also fits the in-sample data well and forecasts the out-sample data satisfactorily. We close the section by presenting the empirical results.

II. 6.4. Estimation Results

Table II. 5 presents the parameter estimates and t-values from the KF estimation.

Table II. 5: Estimation Results

Parameters	Estimates	t-values
OBSERVATION EQUATION PARAMETERS		
Control Variables		
<i>Trend in Attractor Revenue (γ_1)</i>	-0.83	-1.77
Online Ad Revenue Growth (γ_2)	9.71	0.65
<i>Year End Ad Revenue Rise (γ_3)</i>	23.72	8.26
<i>Year Beginning Ad Revenue Drop (γ_4)</i>	-24.09	-8.36
Variance Parameters		
<i>Attractor Revenue Std Deviation (Observation Noise) (σ_A)</i>	0.78	4.68
<i>Suitor Revenue Std Deviation (Observation Noise) (σ_S)</i>	0.0001	0.03
<i>Observation noise covariance (σ_{AS})</i>	11.88	15.20
TRANSITION EQUATION PARAMETERS		
Carry-Over Terms		
Attractor Revenue Carry-over (λ_A)	0.25	2.39
Suitor Revenue Carry-over (λ_S)	0.81	12.19

Parameters	Estimates	t-values
CME's		
<i>Attractor Cross-Market Effect (θ_{AS})</i>	0.42	2.54
<i>Suitor Repercussion Cross-Market Effect (θ_{SA})</i>	0.11	1.74
Marketing Effectiveness		
<i>Effectiveness of Attractor -Directed Marketing (β_A)</i>	4.69	3.40
<i>Effectiveness of Suitor-Directed Marketing (β_S)</i>	2.95	1.84
Variance Parameters		
<i>Attractor Revenue Transition Noise Std Deviation (v_A)</i>	-1.90	-15.15
<i>Suitor Revenue Transition Std Deviation ($v_S \times 10^8$)</i>	0.001	0.001
Maximized Log- Likelihood = -495.48		

Control Variables: The estimated $\gamma_1 = -0.83$ ($p < 0.10$) indicates a declining trend in attractor revenues. The coefficient γ_2 capturing the influence of the online ad-revenue growth on the firm's attractor revenues is not significant, possibly because the older target audience of the newspaper (> 50 years) are less influenced by the Internet. The significant estimates γ_3 and γ_4 ($p < 0.01$) suggest seasonality in suitor revenues. Specifically, we find a statistically significant increase in suitor revenue in the Thanksgiving and Christmas season followed by a drop-off in the beginning of the year. This finding comports with the experience of many small newspapers in the U.S; for example, the *Monroe County Advocate* designs a Christmas Carol supplement to accommodate more ad-space during holiday months because about 41% of news readers find ads most helpful during shopping-sales (Newspaper Association of America Report, 2006).

Cross-Market Effects: We find that the attraction effect (θ_{AS}) and the suitor effect (θ_{SA}) are *both positive*, suggesting that this particular newspaper is a *reinforcing platform*. Positive

suitor effects suggest that, unlike T.V. viewers who have been found to be ad-averse (Wilbur, 2008), our newspaper's readers value advertising. This finding could be explained by several factors: (i) newspapers are a high-attention medium not suitable for multi-tasking; (ii) the newspaper ads are "keepable" since they can be cut out and used at a later period; and (iii) newspapers are viewed as a less-intrusive and more trustworthy source of information (Conaghan, 2006). Additionally, the magnitude of the attractor effect ($\theta_{AS}=0.42$) is almost four times that of the suitor effect ($\theta_{SA}=0.11$), suggesting that a larger pool of attractors is highly valued by the suitors.

Sales Carryover effects: Both parameters representing sales carryover effects, i.e. the attractor carryover coefficient (λ_A) and the suitor carryover coefficient (λ_S) are positive and significant ($p < 0.05$). Higher carryover values imply that current marketing efforts generate revenues for extended periods of time. A high value of sales force carryover λ_S (0.81) is explained by the fact that many local retailers and department stores buy weekly ad space for an extended period of time aiming to inform readers about different sales during the season (Center for Entrepreneurship, 2008). A low value of $\lambda_A = 0.25$ suggests that newly acquired attractors do not stay with the newspaper for extended periods of time. This finding is consistent with the general trend of local readers not finding enough community-content in the newspaper. Local community news is the main differentiating advantage of a local newspaper; but it has gone down by 8% in the last year in US newspapers (Project for Excellence in Journalism Report, 2008).

Marketing effectiveness and elasticities: The effectiveness of newsroom investments on attractor revenues (β_A) and sales force on suitor revenues (β_S) are both positive and significant. Furthermore, the magnitude of β_A (4.69) is about 1.6 times that of β_S (2.95).

How do these estimates contribute to the magnitudes of their respective elasticities? Due to the presence of the two CMEs (θ_{AS} and θ_{SA}), marketing investments towards one end-user group (e.g. attractors) has a direct effect (on attractor demand) and indirect effect (on suitor demand). Thus, our analysis provides empirical support for *cross-market indirect elasticities* (which are distinct from indirect elasticities due to interaction effects between marketing variables, e.g., Naik and Raman 2003; Narayanan et al 2004).

Table II. 6 presents the direct and indirect long-term elasticities of newsroom and sales force investments, respectively.

Table II. 6: Direct and Indirect Elasticities of Marketing

Marketing Variable	Revenue	Nature of Effect	Elasticity Expression	Elasticity*
Newsroom	Attractor	Direct	$\frac{(1 - \nu) \beta \sqrt{u}}{2A[(1 - \nu)(1 - \nu) - \theta_{SA} \theta_{AA}]}$	0.36
	Suitor	Indirect	$\frac{\theta_{SA} \beta \sqrt{u}}{2S[(1 - \nu)(1 - \nu) - \theta_{SA} \theta_{AA}]}$	0.24
Salesforce	Attractor	Indirect	$\frac{\theta_{AA} \beta \sqrt{v}}{2A[(1 - \nu)(1 - \nu) - \theta_{SA} \theta_{AA}]}$	0.13
	Suitor	Direct	$\frac{(1 - \nu) \beta \sqrt{v}}{2S[(1 - \nu)(1 - \nu) - \theta_{SA} \theta_{AA}]}$	0.27

* Elasticities evaluated by using the mean values of u, v, A and S and the estimated parameter values.

As Table II. 6 shows, the direct elasticity of newsroom investments (0.36) is 1.33 times that of the direct elasticity of sales force effort (0.27), and the indirect elasticity of newsroom investments (0.24) is 1.84 times the indirect elasticity of sales force effort (0.13). Lastly, the overall elasticity of the newsroom investment (0.60) is 1.5 times that of the sales force (0.40). These results are not only valuable to the newspaper firm in question but also have some important implications for the daily newspaper industry in general. Specifically, many newsrooms of newspapers have experienced progressive cutbacks in recent times (Rosentiel and Mitchell, 2004). However, if warranted, cutbacks should be made in the investments that possess lower—not higher—overall elasticity. Thus the trend of newsroom cutbacks suggests that managers may be ignoring their cross-market consequences that can be detrimental to total revenues and profit.

In sum, this empirical analysis shows that the proposed platform sales response model is supported by the market data, furnishes strong evidence of the presence of CMEs, and sheds light on indirect marketing elasticities induced by CMEs. Thus, based on the theoretical and empirical results, newspaper managers should systematically estimate response models that incorporate cross-market effects to make informed marketing investment decisions.

II. 7. Planning the Marketing-Investment Mix: A Model-based Decision Aid

II. 7.1. Problem Motivation and Context:

We focus on the development and application of an implementable model-based system that can assist a daily newspaper's corporate marketing managers determine precisely how much

they should expend on marketing efforts directed at attractors (readers) and suitors (advertisers) over a time- horizon. The corporate managers of the newspaper company from whom we acquired our data sought guidance on the profit-maximizing levels of investments in news quality (to maintain and build their readership) and their advertising-space sales force. In general, this is a critical issue for all local daily print newspapers. Although local dailies maintain their status as monopolists, there is erosion in their primary demand as reflected by diminishing household penetration in the recent years (Meyer, 2004). This has prompted questions about which kinds of investments actually build and maintain revenue (Rosentiel and Mitchell, 2004). In practice, many newspapers appear to view investments in the newsroom, i.e., news quality as costs, and are cutting back on them in order to improve profits (Newspaper Employment Census, 2003). This trend of newsroom cutbacks, however, worries researchers in the area who see it as myopic as it ignores (a) the long-run impact of such investments (through λ_A and λ_S in our model) (Lacy and Martin, 2004); and (b) how reduced newspaper quality would lose readers which in turn would reduce advertising revenue (through θ_{AS} and θ_{SA} in our model) (Meyer, 2004). The proposed model-based decision-aid described below accounts for both long-term effects (λ s) and CMNEs (θ s) in deriving optimal marketing-investment trajectories over any decision-horizon specified by corporate management.

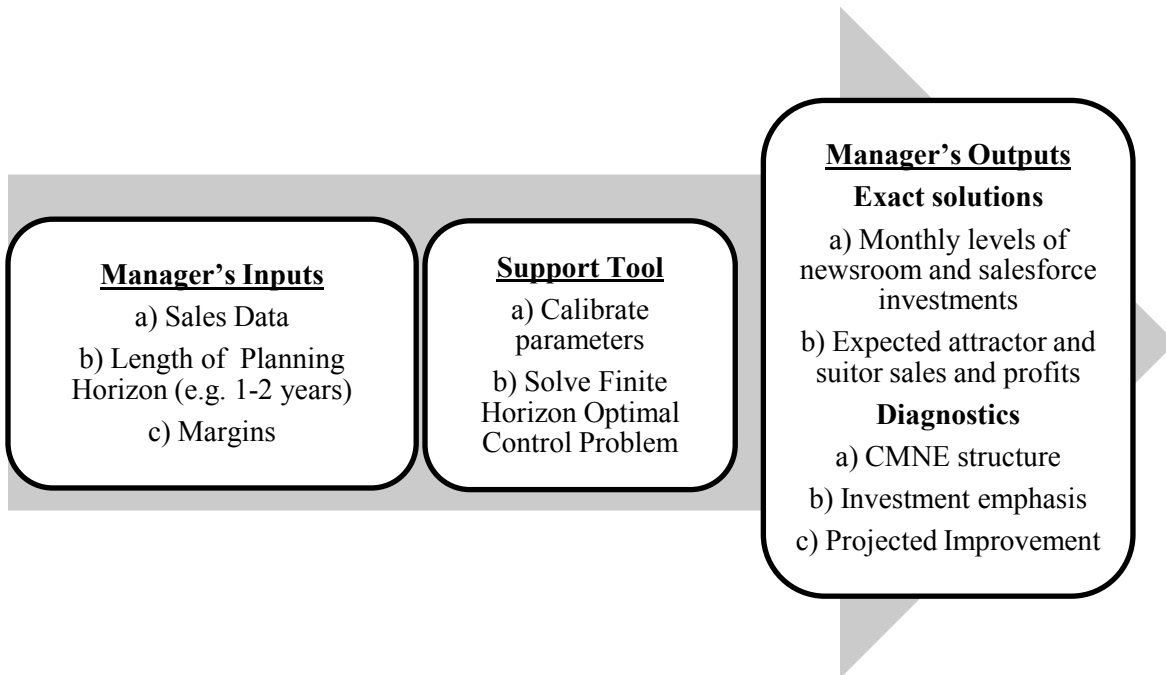
II. 7.1. Description of Model-Decision Aid:

The proposed decision aid falls in the class of *data-driven* marketing management support systems (MMSS) aimed at assisting an *analytic decision-maker* optimize a marketing practice (Wierenga, Van Bruggen and Staelin 1999). It delineates the necessary data inputs to be

assembled by the decision-maker, provides procedures to (a) calibrate the appropriate market response model; (b) utilize this estimated response model with financial data inputs to derive optimal marketing investment trajectories over the specified planning horizon; and (c) display outputs of these solutions, their outcomes, and other diagnostics to assist final decision-making. Similar MMSS applications proposed in the past include the design of optimal advertising schedules (Naik, Mantrala, Sawyer 1998), promotion calendars (Silva-Risso, Bucklin and Morrison 1999) and pricing decisions (Hall, Kopalle, Krishna 2003).

Figure 3 provides a diagrammatic representation of the decision-aid. The main components of the system are the managerial inputs, the estimation and optimal control tool and the managerial representation of outputs.

Figure I.3: Decision Support Tool



Managerial Inputs: In addition to historical data on sales and marketing investments, and average margins from sales to subscribers and advertisers, the decision-aid takes into account the planning horizon of the manager. Planning horizons can be short-term (6-12 months) or medium to long-term (2-3 years). (3 years represents a fairly common managerial-planning horizon (McDonald and Keegan, 2001))

Support Tool: The first step in the support tool is to calibrate the parameters describing the system. This follows the procedure described in the empirical analysis in the previous Section. Using the calibrated parameters, the next step involves deriving the solution of a finite-horizon optimal control problem. For a planning horizon of length T periods, the objective of the problem is to find the profit-maximizing policy of marketing towards the attractors ($u^*(t), t = (1, T)$) and suitors ($v^*(t), t = (1, T)$). The problem is formally specified as follows:

$$\text{Max } J = \int_0^T e^{-\rho t} \Pi(A(t), S(t), u(t), v(t)) dt \quad (22)$$

s.t.

$$\Pi = m_A A(t) + n_S S(t) - c_A u(t) - c_S v(t) \quad (23)$$

and

$$\begin{bmatrix} \frac{dA}{dt} \\ \frac{dS}{dt} \end{bmatrix} = \begin{bmatrix} -(1 - \alpha_A) & \theta_{SA} \\ \theta_{AS} & -(1 - \alpha_S) \end{bmatrix} \begin{bmatrix} A \\ S \end{bmatrix} + \begin{bmatrix} \beta_1 \sqrt{u_t} \\ \beta_2 \sqrt{v_t} \end{bmatrix} \quad (23)$$

The solution procedure is provided in Appendix A. We focus on the managerial outputs that we can provide with the solutions of the problem.

Managerial Outputs: The type of output that a model-based decision aid should produce should be closely aligned to the type of decision the manager is expected to make (Eisenstein and Lodish, 2002). Towards this end, we provide two types of solutions. The first set of solutions are called the *exact* solutions; these are the continuous optimal control path $u^*(t)$ and $v^*(t)$, predicted attractor and suitor sales paths $A^*(t)$ and $S^*(t)$ and predicted optimal profit path $\pi^*(t)$ which are obtained from the solutions in Step 2.

However, it is unusual for managers to follow the *exact trajectory* due to many organizational and environmental issues. Therefore, managers need *directional* guidance that summarizes the basic takeaways from the continuous solutions (Eisenstein and Lodish, 2002). Therefore, we provide diagnostic outputs for the platform manager. The key diagnostic outputs include whether the platform is of the reinforcing/counter-active type, and whether the current managerial marketing allocation is in line with the average values of the exact solutions. These provide a manager with the basis to make a decision.

II. 7.2. Illustration

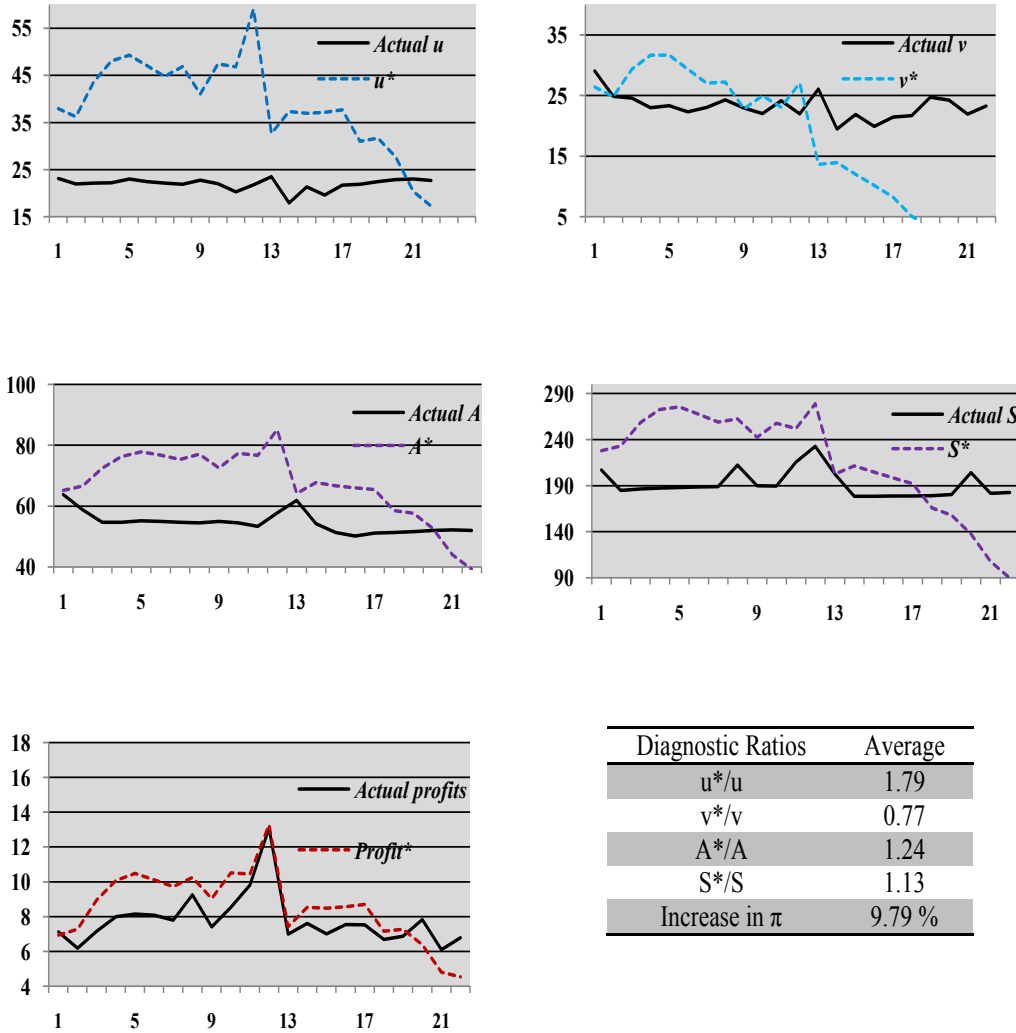
We used the data from the same company to illustrate the profit benefits of optimal planning in the following way.

- 1) We chose the first 96 months of the data for model calibration and the last 24 months as the implementation period.

- 2) Using the margins values for each of the 24 months and calibrated estimates for the 96 month period, we applied Step 2 of our model-decision aid to compute the optimal trajectories of $u^*(t)$ and $v^*(t)$ for the 24 month period and the associated optimal attractor and suitor trajectories $A^*(t)$ and $S^*(t)$ and optimal profits trajectory $\pi^*(t)$.
- 3) Since our cross-validation exercise in the empirical analysis (Section II.6.3) suggested good forecasting ability, we compared the optimal policies $u^*(t)$, $v^*(t)$, associated revenue $A^*(t)$, $S^*(t)$ and profits $\pi^*(t)$ with the actual policies $u(t)$ and $v(t)$, associates revenue $a(t)$ and $S(t)$ and profits $\pi(t)$

Figure 4 briefly summarizes our exact and diagnostic results by showing the actual vs. optimal plots of the trajectories and providing a summary table of the average results from the chosen period. From the descriptive statistics shown earlier, the firm's actual allocation towards u and v was about even. As we demonstrated in the empirical analysis, the overall elasticity of u was 1.5 times that of v due to the effectiveness and CMNE parameters. In line with the intuition obtained from the elasticities, one would expect that u^* should be set higher than and v^* should be set lower than their current allocations. This is reflected in the comparison plots of u^* and v^* with their respective actual values.

Figure I.4: Illustration: Optimal Investments, Revenue and Profit Paths



The plots suggest that u^* should be generally higher than actual, and v^* should be lower than actual values over much of the horizon. The forecasted A^* , S^* and π^* plots document the revenue and profit benefits that can be realized at each time period in the horizon.

As far as diagnostics go, we would recommend a change in the current allocation policy. Specifically, the actual vs. optimal averages suggest that the manager is over-spending in the salesforce ($v^*/v = 0.77$) and under-spending in the newsroom ($u^*/u = 1.79$). The potential benefits from optimal spending are quite significant; attractor revenue can potentially increase by 24%, suitor revenue by 13% and overall profits by 9.79%.

We conclude this section by noting that the newspaper could have achieved better results following the model-based solutions. More generally, other newspapers in the same firm as well as platforms in different industries could use the same model-based decision tool to plan their marketing investment budgets and allocations for short, medium or long-term planning horizons.

II. 8. Conclusion

Since many firms rely heavily on marketing, managers have the responsibility to plan their investment budget and its allocation optimally and demonstrate that these investments generate appropriate returns for the firm. Although considerable research on this topic exists, the literature so far has largely ignored the marketing budgeting allocation problem of platform firms operating in two-sided markets characterized by cross-market effects (CMEs). This gap in research exists despite the reality that platform firms are not only pervasive across the modern business landscape, but also invest heavily in marketing (Evans and Schmalensee, 2007).

Our research contributes to the domain of marketing budgeting and allocation planning by investigating two-sided platform firms' marketing decisions both theoretically and empirically. Specifically, we develop normative budgeting and allocation rules using a proposed

two-sided dynamic sales response model, and estimate and validate the proposed model using data from an archetypal platform firm, namely, a daily newspaper company whose two end-user groups of interest are readers and advertisers.

We derive five new propositions that show how optimal marketing investment strategies towards each end-user group of a platform firm depend on the carryover dynamics of both markets as well as cross-market effects (CMEs). Our analyses show that it is crucial for platform managers to take both effects — CMEs and carryover — into account while making decisions. Specifically, CME structures may imply either an increase in marketing investments in the case of reinforcing platforms or a conservative approach that carefully weighs the gain from adding suitors against the loss of some attractors in counteractive platforms when setting marketing investment levels. We also show that optimal marketing allocation rules for platform firms must account for both the own-market and cross-market benefits of marketing efforts toward each end-user group. Specifically, we show that there may be situations where platform firms should invest heavily in marketing to end-user groups even when they provide low sales margins.

Empirically, our analysis of the longitudinal data from the daily newspaper firm reveals the presence of dynamic CMEs between the readers and advertisers of this newspaper. Our findings imply that CMEs are important in the estimation of marketing effort-sales elasticities in platform firm settings. More specifically, we find that the presence of CMEs substantially increases the net worth of the newspaper's spending on newsroom quality as this investment attracts readers and in turn higher advertiser revenues.

Finally, we build an implementable model-decision aid that allows a platform firm manager to optimally plan the marketing investment mix for any decision horizon. Since many operational and behavioral difficulties are likely to impede implementation of the *exact* policies, we provide managers with diagnostic checks to compare their current policies with the suggested optimal policies. Using a hold-out sample of a forecasting model, we show that the newspaper firm we are collaborating with could increase profits by increasing emphasis in the newsroom compared to the sales force.

Thus, consistent with the thrust of recent conceptual work in journalism and media economics (Rosentiel and Mitchell, 2004), our findings support the case for increasing investments in news quality, which is contrary to what many troubled newspaper companies are doing today. We hope newspaper companies use our proposed model-based approach to determine the marketing budget and its allocations in both reinforcing and counteractive platform markets.

CHAPTER III: BENCHMARKING MEDIA-PLATFORMS: A METHOD AND APPLICATION TO DAILY NEWSPAPERS

III.1. Introduction and Overview

Productivity 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). Examples of DMUs can be *firms* within an industry (Tone and Tsutsui 2008), *production-facilities* within a vertically integrated conglomerate (Ross and Droge 2002) or *geographic-territories* such as the sales districts that salespeople operate in (Horsky and Nelson, 1996). 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).

Benchmarking is one of the most popular management tools in the world and has become a primary instrument in firms' process and capability improvement efforts (Vorheis and Morgan, 2007). The marketing literature has also seen a number of benchmarking applications. Examples include the benchmarking of marketing divisions of high-technology firms (Dutta, Narasimhan and Rajiv 1999), salesperson performance (Parsons, 2004), advertising departments of firms (Luo and Donthu, 2005) and retail outlets of firms (Gauri, Pauler, and Trivedi, 2008; Kamakura, Lenartowicz, and Ratchford 1996).

This chapter focuses on the issue of benchmarking DMUs in the *media* industry (e.g. newspapers, television stations, radio stations). There are three substantive reasons for this research focus. *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 85 daily newspapers and nearly 900 non-daily newspapers that each function as independent DMUs¹. Productivity benchmarking could serve as a way to provide alert, timely, and accurate guidance to DMUs performing below the mark. *Second*, recent years have seen a wave of debatable consolidation and deconsolidation decisions by media-firms. For example, *Clear Communication Inc.* grew to dominate the US radio market by acquiring DMUs from nearly 70 companies. Such acquisitions of DMUs have led to criticism in the industry since not all DMUs were considered strategic assets by analysts (Foley 2006, *The Independent*). Benchmarking is of value during such *merger and acquisition situations* when consolidating firms seek to replace/discard some of their poorly performing DMUs since it provides an assessment of each DMU's efficiency (Ross and Droge, 2002). Third, some media-industries such as the daily newspaper industry sorely need guidance on *efficient* allocation of resources given they are going through troubling economic times due to dwindling circulations (e.g., Bughin and Poppe 2005) and the threat of internet advertising. 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 productivity of media firms.

Besides the above substantive reasons, we are motivated by the fact that the media-firm's business model makes the benchmarking problem methodologically challenging. Specifically, media firms are typically involved in the business of *communicating news, information or*

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

entertainment to one group of consumers while sustaining themselves through *advertising revenue* from a second group. The second group (e.g. retailers) uses the media-firm as a *platform* to advertise their messages to the first group (e.g. readers) and pays the media-firm to have this access. Media-firms are thus examples of *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). Henceforth in this chapter, we will use the terms *media-platform* to refer to such firms. The two-sidedness that a media-platform faces means there are at least three challenges that an appropriate benchmarking approach must take into account.

1. *It should produce efficiency scores at the department-level:* The very sustenance of any two-sided platform is tied to how well it can retain *both* consumer groups such as readers and advertisers (Evans, 2003)². It is frequently observed that if a media-platform (e.g. newspaper) loses its appeal to one consumer group (e.g. readers), it is likely to lose the other group (e.g. advertiser) to competition (Picard, 1994). Since the *tasks* performed in acquiring and retaining a consumer group are very different, media-platforms are usually divided into departments (e.g. circulation and salesforce) that focus on different consumer groups (e.g. reader and advertiser) (Warner and Buchman, pg. 13-15). In some organizations, it is possible that some departments within the firm could be much more efficient in building and maintaining their designated end-user group than others. Assessing this with the use of department-level efficiency scores in a media-platform is important. This is because of the repercussions of the loss of one end-user group (that a department is responsible for) on the retention of the other.

² A platform can only increase social surplus when three necessary conditions are true: (1) distinct groups of customers exist; (2) members of at least one group wish to access the other group and 3) the platform can facilitate the access more efficiently than bi-lateral relationships between the members of the groups (Evans, 2003).

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). This feature of one departmental output being another's input may be observed even in some industrial settings, e.g. in electric power companies, the power generation department's output (electric power) is used by the transmission department to produce its output (electricity distribution lines). However, in the media-platform, outputs could also be *mutually inter-linked*, i.e. each department's output could serve as input to the other. For example, the journalism literature suggests that the content offered to media consumers is also shaped by advertising since it offers advertisers a more targeted vehicle to reach prospective consumers (Hamilton, 2004)³. This is less frequently observed in one-sided market settings than two-sided market settings. Any benchmarking analysis of media-firms must therefore take this key feature into account.
3. *It should be capable of statistical inference about the impact of efficiency:* Numerous factors (e.g. luck, weather) could influence the impact of the conversion of each media-firm department's input into output. It is useful to control for them while performing benchmarking analyses. Specifically, a stochastic media-benchmarking model will partial out the role of random error in the conversion of inputs into outputs (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 firm's outputs (e.g. Arnold et al 1996). A complex and inter-connected structure, the media-

³ 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".

platform is often faced with debates over which department contributes most to its success (e.g. DeLorme and Fedler, 2003). Obtaining efficiency scores at the departmental level with statistical validity provides a scientific basis for resolving such arguments.

Examination of several commonly applied benchmarking techniques (e.g. Data Envelopment Analysis (DEA) [Charnes, Cooper, and Rhodes, 1978], Stochastic Frontier Analysis [Aigner et al. 1977]) reveals that no *available* method handles *all the three challenges* noted above. The first objective of this chapter is therefore to develop a suitable approach to benchmark media-platforms by addressing all three challenges simultaneously. Specifically, we combine the relatively new techniques of *Network DEA* (NDEA) and *Multivariate Sliced Inverse Regression* (MSIR) and adapt them to our problem in a fashion that enables us to address all three challenges mentioned above. Even though our motivation is to benchmark media-platforms, our proposed approach is fairly general and can also be used in benchmarking other (non-media) two-sided platforms (e.g. shopping malls). The second objective of this chapter lies in empirical demonstration/validation of the approach via an application 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. While doing so, we also demonstrate how the proposed approach outperforms applications of existing approaches applied to platform-firms. In sum, this chapter offers a new approach for benchmarking platform firms while offering new substantive guidance to the newspaper industry.

The organization of this chapter is as follows. We first review available procedures for benchmarking and their limitations with respect to the platform-firm benchmarking context (III.2.1). We then describe our proposed approach and highlight its advantages (III.2.2). Next we describe the organization of print newspapers and the data we have regarding their inputs and output (III.3.1). Subsequently, we apply our approach to these data and compare the results with those of extant approaches in dealing with the benchmarking problem (III.3.2-III.3.4). To obtain more managerial insights, we investigate some determinants of our derived newspaper firm efficiency scores and 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 (III.4).

III.2 Development of an Appropriate Benchmarking Procedure

In this section, we describe the commonly used approaches for benchmarking and highlight their limitations in addressing the benchmarking challenges posed by media-platforms. We then proceed to develop a comprehensive approach that addresses the challenges.

III.2.1 Commonly Used Approaches for Benchmarking

Data Envelopment Analysis (DEA)

This is a well-known mathematical programming-based technique that is popularly used for benchmarking. DEA 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 is preferred so that a *scalar efficiency metric* can be obtained. Rather

than use arbitrary or *a priori* weighting schemes that have shown to have several drawbacks (see Kamakura et al. 1996), 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, given any set of weights, a DMU's efficiency is the weighted ratio of outputs to inputs. 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). The optimization problem has the constraint that for the optimally chosen set of weights, a DMU's own efficiency as well as all of the competing DMUs' efficiencies cannot exceed 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). The details pertaining to the exact calculation of the efficiency score are provided in the Technical Appendix B. A DMU is 100% *efficient* if the weighted ratio score is 1 and inefficient otherwise.

The fact that DEA is a non-parametric technique that requires no functional form assumptions about the production function make it an appealing prospect. Additionally, DEA can be used to handle multiple outputs and multiple inputs with ease. Not surprisingly, the literature on DEA in marketing is vast (e.g. Horsky and Nelson 1996; Luo et al 2006). DEA has been used in numerous other applications such as banking, management, and operations (see Emrouznejad and Thanassoulis 2001 for an exhaustive list).

Column 2 in Table III.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, 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 completely ignore the two-sided feature of the media-platform, i.e. the relatedness of outputs. Next, by design, outputs and inputs are not allowed to be interrelated in the technique and hence it cannot recognize the idea that outputs of one department may be inputs to another in a media-platform. Finally, since this is purely deterministic, it cannot provide statistical inference about the impact of efficiency (Donthu and Yoo 1998) and hence cannot address the third challenge. Therefore, it is not a comprehensive tool for our purpose (see Table III.1).

Table III.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

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).

Performing benchmarking through NDEA involves the specification of the networked input-output structure within a DMU and then the solution of a linear program similar to that of standard DEA. The details pertaining to the calculation of the efficiency scores through NDEA are provided in Appendix C. 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 are comprised. The recruiting department uses salaries as inputs to produce player position-talent. The production department uses salaries as well as the player talents

acquired to (outputs form 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 the area of banking (Avkiran 2009) and transportation sectors (e.g. Yu and Lin 2008).

Column 3 in Table III.1 evaluates the use of NDEA as a tool for benchmarking media-platforms. To apply NDEA 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 and 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 Seton (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 III.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

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

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

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

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 is also a very popular approach and has seen several applications in marketing (e.g. Kamakura et al. 1996; Dutta et al 1999, Luo and Donthu 2004).

Column 4 in Table III.1 evaluates the use of SFA as a tool for benchmarking media-platforms. Similar to DEA, one could again 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 ignore

the relatedness of outputs and thereby not address the second challenge in questions. However, one of the strengths of SFA is that it 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 a 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, inference still needs *a priori* assumptions about the shape of $f(\cdot)$ and the distribution of the composite error term ε^k . In light of these limitations, SFA is not suited to the media-platform context.

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 captures the effect of efficiency (ρ^k) on the firm's composite output CY^k .

The basic 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 III.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 benchmarking tool for the media-platform context.

III.2.2 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, our approach uses the same intuition as the approach proposed by Arnold et al (1996), i.e. we also 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.

Use of NDEA instead of DEA in Stage 1:

The first stage of the two-stage approach involves the evaluation of efficiency scores of each media-firm DMU. Our comparison in Table III.1 showed that NDEA was better suited than DEA in this regard. Therefore, we propose the use of NDEA for Stage 1.

Use of Multivariate Sliced-Inverse Regression (MSIR) instead of Canonical Correlation (Part 1) and the Cobb-Douglas (Part 2) 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 a semi-parametric approach, 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

$$y = g(\alpha_1 X_1, \dots, \alpha_k X_k, \varepsilon) \quad (5)$$

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 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

$$\begin{aligned}
 \theta Y &= \zeta(\alpha X, \dots, \alpha_k X, \varepsilon \\
 \theta_l Y &= \zeta(\alpha_l X, \dots, \alpha_k X, \varepsilon \\
 &\dots \\
 \theta_l Y &= \zeta(\alpha X, \dots, \alpha_k X, \varepsilon
 \end{aligned} \tag{6}$$

The Technical Appendix (D) 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 etc⁴. *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, 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,

⁴ See Naik, Hagerty and Tsai (2000) for an exhaustive comparison of SIR and popular dimension reduction techniques

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 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 $g()$ where $COMP_Y = g(COMP_X)$ such that it obtains the lowest value 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.

Column 6 in Table III.1 evaluates the use of our two-stage (NDEA + MSIR) technique as a tool for benchmarking media-platforms. We can see that the use of NDEA allows our tool to address the first two challenges effectively, i.e. we can obtain sub-DMU and DMU efficiency scores while recognizing the relatedness between the outputs. We can also obtain inference about the impact of increase of sub-DMU efficiency on the outputs of the media-platform. Therefore, our new approach can also address the third challenge of statistical inference.

In sum, our newly developed approach theoretically addresses all the benchmarking challenges of the media-platform simultaneously. Next, we demonstrate the empirical applicability of our approach using data on U.S. print newspapers.

III.3. Empirical Illustration

III.3.1. Data Setting

Our data for the purpose of this research 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 80,000. 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

- *Full-time Employees*: This captures the number of full-time employees in each department
- *Part-time Employees*: This captures the number of part-time employees in each department
- *Expenditure on Equipment*: 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)

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 III.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 about the same in 1999 and 2002 (58% and 59% respectively) and in keeping with industry norms for the ratio (e.g. Peer and Nesbitt, 2004). However, the large standard deviations around these numbers shows that there is significant variation in the norms used by individual newspaper managers within year. Specifically, the ratio of content 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.

Table III.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

		Year 1999		Year 2002	
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

III.3.2. 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 III. 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 III. 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). The most common distinction between ads is whether they are price-oriented or not.

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 III. 3).

Table III. 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 (#) Retail Ad Revenue (\$) National Ad Revenue (\$) Classified Ad Revenue (\$)	-NA-	

III.3.3. 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.

Efficacy of NDEA Over DEA

The mean efficiency scores of the newspapers in the Years 1999 and 2002 are provided in Table III. 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 III. 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

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

Table III. 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. For example, Harris (1995) states the usefulness of benchmarking in a simple and elegant manner

“Put quite simply, benchmarking is the art of finding out-in a completely straightforward and open way-how others go about organizing and implementing the same things you do or that you plan to do. The idea is not simply to compare your efficiency with others but rather to find out what exact process, procedures, or technological applications produced better results. And when you find something better, to use or copy it-or even improve upon it still further”

In this vein, the efficacy of a good benchmarking technique rests in its ability to single out a handful of top performers. Table III. 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 lesser and is probably more meaningful.

Table III. 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

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 III. 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.

Table III. 6. Correlation with Profits

Year	Year		Year	
	1999		2002	
Method	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

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

Our first substantive result is a comparison of departmental efficiency scores across the newspapers. Referring back to Table III. 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). In fact, the average efficiency scores of the newsroom are nearly 1.5 and 1.25 times larger than the other department's average efficiency scores in 1999 and 2002 respectively. This could be due to the fact that the newspaper story composition is fairly standardized in the industry. Specifically, the choice story topics, writing style and the geographic and demographic focus of newspapers is fairly homogenous in the newspaper business (Peer and Nesbitt, 2004). In contrast, the media salesforce faces a much more uncertain environment since their job involves selling the *expectation of future success* to the potential advertiser (Warner and Buchman 1991).

Another reason for high newsroom efficiencies could stem from the fact that newsrooms tend to report the least turnover in the newspaper. Recent research finds that the yearly newsroom turnover (15%) is much lower than the sales force turnover (23%) (Duke and Nesbitt, 2004). Keeping turnover at moderate levels has shown to lead to better organizational performance (Meier and Hicklin, 2007). In contrast, high levels of turnover may lead to less efficient departments.

We next study the distribution of good and bad performers in 1999 and 2002 using the *overall* NDEA scores. Table III. 7 shows that the overall industry has a mean efficiency score of 0.53 in 1999 and 0.63 in 2002. The dispersion around the mean score is also worthy of attention. Specifically 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, and hence the lowering of inputs to departments (Meyer, 2004), resulted in higher efficiency scores in 2002.

Table III. 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

Next, we note that firms performing on the efficient frontier, i.e. firms with a 100% NDEA score are significantly more profitable. Table III. 8 shows these results. Specifically, in the year 1999, we note that firms identified as being 100% efficient report \$4.70 million in profits while those that obtained significantly lower profits (specifically, they obtain average profit of \$2.70 million).

Table III. 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

Why are some newspapers more efficient than others?

The above NDEA analyses with the newspaper data shed light on the usefulness of NDEA as a benchmarking technique and highlighted the differences in the efficiency scores and profits of various departments and newspapers in the samples studied. However, they do not shed light on some of the reasons for the high/low efficiency scores. 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 salesforce) of each newspaper with seven variables that we created from the IPA dataset. These seven variables serve as profiling variables that provide some detail about the size of the newspaper and its strategic priorities. The variables created are:

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)

The first variable 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, e.g. a newspaper with a larger number of support staff is better-endowed than one without. Variables 4 through 7 represent strategic choices that a newspaper makes with respect to employees (Variable 4), and newspaper composition (Variables 5-7). We then performed a two-step cluster analysis⁶ of the 7 profiling variables together with the 3 departmental efficiency scores.

The two-step cluster Analysis procedure is an exploratory tool designed to reveal natural groupings (or clusters) within a data set that would otherwise not be apparent. The two steps include a) the construction of a set of nodes using the information on each case (i.e. the 10 variables) and b) grouping the nodes into clusters based on an agglomerative clustering algorithm (Chiu et al. 2001). To determine the number of clusters that is "best", each of these cluster solutions is compared using Schwarz's Bayesian Criterion (BIC) or the Akaike Information Criterion (AIC) as the clustering criterion. BIC always decreases as the number of clusters increases. However, the improvement as measured by the BIC change may not be worth the increased complexity of the cluster model. In such situations, the common practice is to use the number of clusters that has a low enough BIC score and most useful explanatory power (e.g. Hennig-Thurau Houston and Sridhar, 2006).

⁶ We used the commercially available software SPSS 16.0 for this purpose

Table III. 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 III. 10. Cluster Analysis Results

Panel 1. Year 1999			
Categories	Cluster 1	Cluster 2	Overall
	Mean	Mean	
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

The results of the cluster analysis for the Years 1999 and Year 2002 are shown in Table III. 9 and Table III. 10. Based on the BIC indices in Table III. 9 and the parsimony of the two cluster solution, we retained the two-cluster solution. From Table III. 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 III. 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.

Next, we see if the seven profiling variables' means can be used to explain the covariates of high efficiency. We especially refer to the profiling variables that show pronounced differences across the *High Efficiency* and *Low Efficiency* clusters.

First, we note that 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 respective 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 of the fact 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 67-33 content to ad-space ratio is correlated with higher efficiencies (Peer and Nesbitt, 2004).

This is rationalized as follows. Readers of local newspapers are shown to be ad-lovers (Sonnac, 2002), i.e. the increase of ad-revenue is actually shown to increase the number of subscriptions to a newspaper (Mantrala et al 2007). Even though increasing the ad-content in a newspaper increase what is termed in the industry as “ad-clutter” (Warner and Buchman, 1991), it is observed that entertainment-oriented publications are shown to be more affected by clutter than news-oriented publications (Ha and Litman, 1997). Bhargava and Feng (2009) show that the optimal proportion of ad to content levels *increases* with *decreasing* sensitivity of consumers to ads. Given that news readers are ad-seeking, the sensible approach of a newspaper would be to set higher levels of advertising 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 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.

In summary, Stage 1 of our analysis sheds light on the distribution of efficiencies in the newspaper industry and some of the profiling variables that help explain these departmental efficiencies. In Stage 2, we quantify the effect of increasing the efficiencies on the outputs produced by the newspaper.

III.3.4. Stage 2: Results of MSIR Analysis

The efficiency scores from the NDEA analysis are a useful diagnostic to study the *level* of inefficiency in each department of the media-firm. Stage 2 is performed to *quantify the impact* that a given level of efficiency has on the output-producing capability of a firm. Stage 2 also accounts for the role of error while gauging this impact.

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 (E) 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 III. 11 present the results of the MSIR model and the estimates of β from the regression of COMP_Y and COMP_X⁸

Table III. 11. MSIR Estimation Results

<i>Panel 11.1 MSIR Estimates</i>						
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

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

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						
		Year 1999 ($\delta = 0.6$)			Year 2002 ($\delta = 0.5$)	
Coefficient	Estimate	Std Error	t-value	Estimate	Std Error	t-value
β	3.854	0.005	755.5 90	5.133	0.007	740.2 80

To obtain a meaningful interpretation of the results in Table III. 11, we used the estimates in the model to calculate a mathematical expression for the % increase in a newspaper output (e.g. ad space sold) given a 1% change in a department's efficiency (e.g. sales force). 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 finding can be explained by the following reasons. First, the operating levels of newsroom efficiency are already 20-30% higher than the efficiencies of the distribution and sales force departments. It is unlikely that any additional increases in efficiencies could lead to a further increase in outputs, i.e. diminishing returns set in on efficiency. Second, it has been conceptualized (Meyer and Kim

2004) and empirically demonstrated (Mantrala et al 2007) that newspapers tend to be under-staffed in the newsroom. Our statistical result might be a manifestation of the idea that on average, the newsroom is already performing as efficiently as it can given it is an under-staffed department.

In contrast, Table III. 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 III. 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*

Table III. 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. This shows that the sales force department can be more efficient by recognizing that consumers search newspapers for certain types of ads that interest them. Hence if the ad-space sold is geographically targeted, credible and provides detailed information to consumers, it can result in increases in subscriptions and higher sales force efficiency.

Prior research on the selling process indicates that selling-situations where the selling-time is fairly limited, i.e. that a firm cannot tell the customer about all of its product's features, the firm can signal the presence of all of these features by allowing the customer to control the information presented in the sales interaction and by choosing the appropriate price (Bharadwaj, Chen and Godes 2008). This means that in the media setting, rather than having presentations initiated by the seller alone, it may be more useful to engage in a dialogue-oriented selling. Additionally, ad-rates in the newspaper industry tend to be fairly rigid for long periods (Mantrala et al 2007). Adopting the Bharadwaj et al (2007) view, allowing the retailer or reader (classified ads) to have some flexibility and control in the ad-rates might lead to a more efficient selling process.

Finally, 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 III. 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.

III.4 Discussion and Conclusions

Contributions

Productivity benchmarking is a critical responsibility of managers since accurate and timely benchmarks are useful in identifying best-practices of companies. Although considerable research on this topic exists, the literature so far has largely ignored the benchmarking problem of media-platforms operating in two-sided markets. It is important to address this gap since certain media-industries need formal guidance in the face of bad economic conditions.

Our research aims at making two contributions to the literature. We delineate three challenges that make the media-firm benchmarking problem a non-trivial and unresolved one. Our first 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.

Several substantive and methodological and substantive results emerge from our analysis. We discuss some implications for media-platforms first.

Implications for Media-Platforms

The massive growth of media advertising has led to the sustenance of many media-platforms, e.g. total spending on advertising in all media in the United States in 2004 was \$141.1

billion (TNS Media Intelligence Report 2005). Frequently, departments of media-platforms are organized so as to perform tasks that mainly serve one consumer group (e.g. reader). The reality is that a media-firm produces a joint product that is simultaneously consumed by both end-user groups. In this unique business model, the outputs produced by one department can greatly enhance the efficiency of the other and any benchmarking analysis must appreciate this key feature. Our methodology embraces this two-sided feature while providing departmental and overall efficiency scores. First, we demonstrate the granular insights that can be obtained from this two-sided view through a series of results focused at the department level. We show that such indices are better predictors of managerial performance and should therefore be used while benchmarking media-firms. Therefore, managers can use our two-stage approach to benchmark media-platforms and in process development efforts that follow.

Implications for Academics

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 applications in the marketing context as well. 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.

Implications for the Newspaper Industry

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. Next, 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. Next 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).

Another way to use the results is to obtain a comparison of a particular department of a DMU (e.g. newsroom) against its counterpart in all other DMUs (e.g. newsroom of all other DMUs). This can provide a manager with the option of improving a specific capability of a newspaper against an industry-benchmark. This could supplement the comparisons we have performed in this chapter.

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: Solution of Finite Horizon Problem

The finite-horizon problem is formally specified as follows:

$$\text{Max } J = \int_0^T e^{-\rho t} \Pi(A(t), S(t), u(t), v(t)) dt \quad (\text{A1})$$

s.t.

$$\Pi = m_A A(t) + n_S S(t) - \dots \quad (\text{A2})$$

and

$$\begin{bmatrix} \frac{dA}{dt} \\ \frac{dS}{dt} \end{bmatrix} = \begin{bmatrix} -(1-\dots) & \theta_{SA} \\ \theta_{AS} & -(1-\dots) \end{bmatrix} \begin{bmatrix} A \\ S \end{bmatrix} + \begin{bmatrix} \beta_1 \sqrt{u_t} \\ \beta_2 \sqrt{v_t} \end{bmatrix} \quad (\text{A3})$$

To obtain the optimal controls, we proceed as follows. We first define the current-value Hamiltonian

$$H = n_A A + n_S S - \dots + \mu \{- \dots A + \lambda_A S + \beta_1 \sqrt{u}\} + \lambda \{- \dots S + \lambda_S A + \beta_2 \sqrt{v}\} \quad (\text{A4})$$

We then apply the Maximum Principle giving the first-order conditions

$$\frac{\partial H}{\partial u} = \dots + \frac{\mu \beta_1}{2\sqrt{u}} \Rightarrow \begin{bmatrix} \mu \\ \frac{\beta_1}{2} \end{bmatrix} \quad (\text{A5})$$

And

$$\frac{\partial \mathcal{L}}{\partial \mu_1} = \dots + \frac{\mu_2 \beta}{2\sqrt{v}} \mu_2 \beta \Rightarrow \left[\begin{array}{c} \mu_2 \beta \\ 2 \end{array} \right] \quad (\text{A6})$$

and the co-state conditions

$$\frac{\partial \mathcal{L}}{\partial \mu_1} = \mu_1 - \frac{\partial \mathcal{L}}{\partial \mu_1} = \mu_1 - n_A + \lambda_1 (1 - \nu_A) - \lambda_2 \theta_{AS} \quad (\text{A7})$$

and
$$\frac{\partial \mathcal{L}}{\partial \mu_2} = \mu_2 - \frac{\partial \mathcal{L}}{\partial \mu_2} = \mu_2 - n_S + \lambda_2 (1 - \nu_S) - \lambda_1 \theta_{SA} \quad (\text{A8})$$

In addition, since the final state values $A(T)$ and $S(T)$ are free (i.e. not fixed), we apply the transversality conditions

$$\mu_1(T) = \mu_2(T) = 0 \quad (\text{A9})$$

This gives us a recursive system of linear differential equations in the state and co-state variables:

$$\begin{bmatrix} \frac{dA}{dt} \\ \frac{dS}{dt} \\ \frac{d\mu_1}{dt} \\ \frac{d\mu_2}{dt} \end{bmatrix} = \begin{bmatrix} -(1-\gamma_A) & \theta_{SA} & 0 & 0 \\ \theta_{AS} & -(1-\gamma_S) & 0 & 0 \\ 0 & 0 & \rho-1-\gamma_A & -\gamma_{AS} \\ 0 & 0 & -\gamma_{SA} & \rho-1-\gamma_S \end{bmatrix} \begin{bmatrix} A \\ S \\ \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \beta_1 \sqrt{u} \\ \beta_2 \sqrt{v} \\ -m_A \\ -m_S \end{bmatrix} \tag{A10}$$

Since the system in Eqn. 30 is recursive, the solution path is obtained in the following steps:

Step 1: Since the co-state system of differential equations is linear and independent of the state variables, we first obtain the optimal values μ_1^* and μ_2^* by solving the system of differential equations pertaining to μ_1 and μ_2 . The solution is given as

$$\mu_1^*(t) = \bar{i}_1 \left\{ 1 + \frac{[(\lambda_A - \gamma_S) - p]e^{r_2(t-T)} - [(\lambda_A - \gamma_S) + p]e^{r_1(t-T)}}{2p} \right\} + \frac{\bar{u}_2 \theta_{AS}}{p} \left\{ e^{r_2(t-T)} - e^{r_1(t-T)} \right\} \tag{A11}$$

and

$$\mu_2^*(t) = \bar{i}_2 \left\{ 1 + \frac{[(\lambda_A - \gamma_S) - p]e^{r_1(t-T)} - [(\lambda_A - \gamma_S) + p]e^{r_2(t-T)}}{2p} \right\} + \frac{\bar{u}_1 \theta_{SA}}{p} \left\{ e^{r_2(t-T)} - e^{r_1(t-T)} \right\} \tag{A12}$$

Where
$$\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} = \frac{1}{[(\rho - 1 - \lambda_A)(\rho - 1 - \nu_S) - \theta_{AS}\theta_{SA}]} \begin{bmatrix} m_A(\rho - 1 - \nu_S) + m_S\theta_{AS} \\ m_S\theta_{SA} + m_A(\rho - 1 - \nu_A) \end{bmatrix}$$
 (A13)

$$\rho = \sqrt{\lambda_A - \nu_S} + \theta_{AS}\theta_{SA}$$
 (A14)

$$r_1 = \frac{(\rho - \nu_A) + (\rho - \nu_S) - \theta_{AS}\theta_{SA}}{2}$$
 (A15)

and
$$r_2 = \frac{(\rho - \nu_A) + (\rho - \nu_S) + \theta_{AS}\theta_{SA}}{2}$$
 (A16)

Step 2: Using Eqns. 10, 11, 16 and 17, we can obtain the optimal control trajectories $u^*(t)$ and $v^*(t)$ as a function of μ_1^* and μ_2^* given as

$$\begin{bmatrix} u^*(t) \\ v^*(t) \end{bmatrix} = \begin{bmatrix} \left[\frac{\mu_1^*(t)\beta_1}{2} \right]^2 \\ \left[\frac{\mu_2^*(t)\beta_2}{2} \right]^2 \end{bmatrix}$$
 (A17)

Step 3: We substitute the optimal marketing trajectories into the state equation to find the predicted optimal attractor (A^*) and suitor sales (S^*) trajectories. To do so, first let the initial values for $A(0)$ and $S(0)$ be A_0 and S_0 respectively. Using the values of μ_1^* , μ_2^* , u^* , v^* , we can solve for the optimal state variables A^* , S^* by solving the system of differential equations pertaining to A^* and S^* from Eqn. 40. This gives us the optimal values $A^*(t)$ and $S^*(t)$ as

$$\begin{aligned}
A^*(t) = (\bar{A} - A_0) & \left\{ 1 + \frac{[(\lambda_A - \lambda_S) - p]e^{q_2(t-T)} - [(\lambda_A - \lambda_S) + p]e^{q_1(t-T)}}{2p} \right\} \\
& + \frac{(\bar{S} - S_0)\theta_{AS}}{p} \left\{ e^{q_2(t-T)} - e^{q_1(t-T)} \right\}
\end{aligned} \tag{A18}$$

And

$$S^*(t) = \left\{ + \frac{[(\lambda_A - \lambda_S) - p]e^{q_1(t-T)} - [(\lambda_A - \lambda_S) + p]e^{q_2(t-T)}}{2p} \right\} \tag{A19}$$

$$+ \frac{(\bar{S} - S_0)(\bar{A} - A_0)\theta_{SA}}{p} \left\{ e^{q_2(t-T)} - e^{q_1(t-T)} \right\}$$

where q_1, q_2 are given by

$$q_1 = \frac{(\lambda_A - \lambda_S) + (\lambda_S - \lambda_A) - p}{2} \tag{A20}$$

and

$$q_2 = \frac{(\lambda_A - \lambda_S) + (\lambda_S - \lambda_A) + p}{2} \tag{A21}$$

And

$$\begin{bmatrix} \bar{A} \\ \bar{S} \end{bmatrix} = \frac{1}{(1-\nu_A)(1-\nu_S) - \nu_{AS}\nu_{SA}} \begin{bmatrix} (1-\nu_A)\frac{\beta_1^2\mu_1^*}{2} + \frac{\theta_{AS}\beta_2^2\mu_2^*}{2} \\ (1-\nu_S)\frac{\beta_2^2\mu_2^*}{2} + \frac{\theta_{SA}\beta_1^2\mu_1^*}{2} \end{bmatrix} \quad (\text{A22})$$

Appendix B. 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)

$$P = \{(x, y) \mid x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\} \quad (\text{B1})$$

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

$$\sum_{i=1}^n \lambda_i = 1 \quad (\text{B2})$$

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

$$x_0 = X\lambda + s^- \quad (\text{B3})$$

$$\text{and } y_0 = Y\lambda + s^+ \quad (\text{B4})$$

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

$$\rho = \frac{1 - (1/m) \sum_{i=1}^m s_i^- / x_{io}}{1 + (1/s) \sum_{r=1}^s s_r^+ / y_{ro}} \quad (\text{B5})$$

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

$$\underset{\{\lambda, s^+, s^-\}}{\text{Min}} \rho = \frac{1 - (1/m) \sum_{i=1}^m s_i^- / x_{io}}{1 + (1/s) \sum_{r=1}^s s_r^+ / y_{ro}} \quad (\text{B6})$$

s.t. Equations B3, B4 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 C. 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

$$x^k \geq \sum_{j=1}^n x_j^k \lambda_j \quad \forall k = 1, 2, \dots, K \quad (C1)$$

$$y^k \leq \sum_{j=1}^n y_j^k \lambda_j \quad \forall k = 1, 2, \dots, K \quad (C2)$$

$$z^k \geq \sum_{j=1}^n z_j^{(k,h)} \lambda_j \quad \forall (k, h) \text{ (as outputs from } k \text{ to other sub-DMU's)} \quad (C3)$$

$$z^k = \sum_{j=1}^n z_j^k \lambda_j \quad \forall (k, h) \text{ (as inputs to } h \text{ from sub-DMU } k) \quad (C4)$$

$$\sum_{j=1}^n \lambda_j = 1 \quad \forall (k, j) \quad (C5)$$

$$\lambda_j \geq 0 \quad \forall (k, j) \quad (C6)$$

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

$$\rho = \frac{1 - (1/m_k) \sum_{i=1}^m s_i^{k-} / x_{io}^k}{1 + (1/r_k) \sum_{r=1}^s s_r^{k+} / y_{ro}^k} \quad (C7)$$

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

$$\rho = \frac{\sum_{k=1}^K 1 - (1/m_k) \sum_{i=1}^m s_i^{k-} / x_{io}^k}{\sum_{k=1}^K 1 + (1/r_k) \sum_{r=1}^s s_r^{k+} / y_{ro}^k} \quad (C8)$$

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

$$x_o^k = X^k \lambda + s^{k-} \quad (C9)$$

$$y_o^k = Y^k \lambda - s^{k+} \quad (C10)$$

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

$$Z^{(k,h)} \lambda = z^{(k,h)} \quad (C11)$$

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

$$\underset{\{\lambda, s^{k+}, s^{k-}\}}{\text{Minimize}} \rho = \frac{\sum_{k=1}^K 1 - (1/m_k) \sum_{i=1}^m s_i^{k-} / x_{io}^k}{\sum_{k=1}^K 1 + (1/s_k) \sum_{r=1}^s s_r^{k+} / y_{ro}^k} \quad (\text{C12})$$

subject to constraints (C9), (C10) and (C11).

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 (C7).

Appendix D. 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

$$y = g(\alpha_1 X, \dots, \alpha_k X), \varepsilon \quad (D1)$$

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

$$\varphi(y) = E[X|y] \quad (D2)$$

Next, we define the matrix

$$\Sigma_\eta = \text{cov}(E[X|y]) \quad (D3)$$

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

$$\Sigma_x \alpha = \lambda \Sigma_x \alpha \quad (D4)$$

$$\lambda_1 > \lambda_2 > \dots > \lambda_K \quad (D5)$$

$$\alpha = \Sigma_x^{-1} \alpha \quad (D6)$$

Where λ_k is the k^{th} Eigen-value, arranged in descending order for $k=1, \dots, K$ and α_k is the corresponding Eigen-vector. To obtain actual estimates of $\hat{\alpha}$ 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

$$\hat{\Sigma}_\eta = \sum_{h=1}^H p_h (\bar{X}_h - \bar{Y})(\bar{X}_h - \bar{Y})' \quad (D7)$$

Where 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 (D7) and the sample covariance matrix Σ_X to obtain the estimates of $\alpha_1, \dots, \alpha_K$ in D4-D6. 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

$$\text{Standard err}(\hat{\alpha}) = \frac{(1 - \hat{\lambda})}{\hat{\lambda}} n^{-1/2} \hat{\Sigma}^{-1} \quad (D8)$$

Multivariate SIR (MSIR)

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

$$Y = g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \quad (D9)$$

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

$$\begin{aligned} \theta_1 Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \\ \theta_2 Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \\ &\dots \\ \theta_l Y &= g(\alpha_1 X, \dots, \alpha_k X, \varepsilon) \end{aligned} \quad (D10)$$

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.

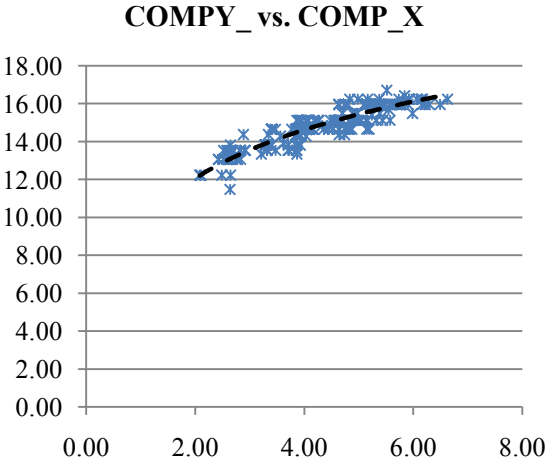
The first canonical covariate usually explains a fair portion of the variance in the Y vector and can be used to reduce Y (Step 2). Canonical correlation itself is simply a special case of univariate SIR. The canonical variates of Y begin the iterative process of reducing X and Y respectively through 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 E 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 E1. Plot of COMP_Y vs. COMP_X Space



This means that transforming the outputs and inputs into logarithms did not capture all the non-linearity in the production function. This would mean that the Arnold et al (1996) assumption would not suffice in our context. To ascertain that there is indeed some more non-linearity, we estimated a series of non-linear models given by $COMP_Y = \dots$ where δ ranged from 0 to 1 in increments of 0.1.

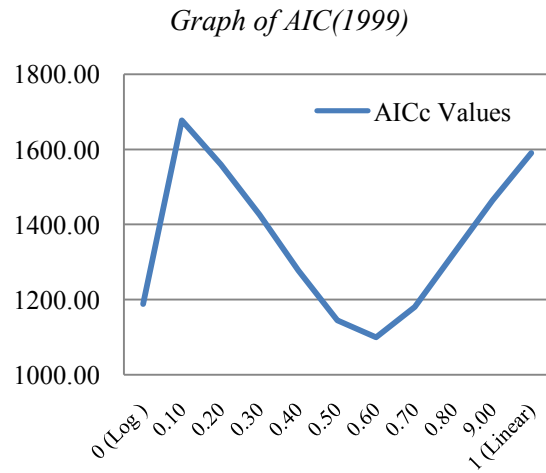
When $\delta = 1$, the relationship between COMP_Y and COMP_X is linear and we can retain the Arnold et al (1996) assumption. However, we found that the AIC minimizing value of δ was 0.6 in the year 1999 and 0.5 in the year 2002 (see Table E1 below).

Table E1 Model Comparison

Panel 1 Comparison for Year 1999

Table of AIC Values (1999)

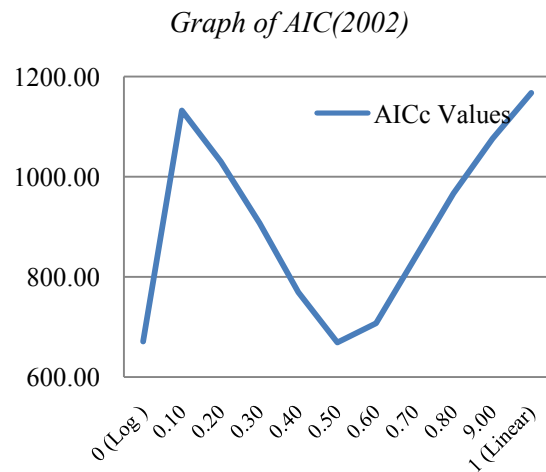
δ	AIC-c Values
0 (Log)	1188.24
0.1	1677.26
0.2	1560.08
0.3	1425.51
0.4	1277.68
0.5	1144.89
0.6	1099.60
0.7	1180.70
0.8	1321.89
9	1464.25
1 (Linear)	1590.47



Panel 2 Comparison for Year 2002

Table of AIC Values (2002)

δ	AIC-c Values
0 (Log)	671.46
0.1	1132.64
0.2	1030.22
0.3	907.57
0.4	769.68
0.5	669.29
0.6	707.56
0.7	837.06
0.8	966.92
9	1076.52
1 (Linear)	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.

VITA

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