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Measuring Arbitrage Opportunities

A Minimum Performance Inefficiency Estimation Technique

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Entrepreneurs respond to opportunities that come in two basic forms: innovation and arbitrage. This article presents a technique called the minimum performance inefficiency (MPI) estimation method that could be used to estimate arbitrage opportunities. The technique has several advantages over the conceptually similar data envelopment analysis (DEA) and other techniques. The authors validate the technique with a well-known data set and illustrate its use based on secondary data from the publishing industry.

The notion of opportunities is central to entrepreneurship research (Shane & Venkataraman, 2000). Entrepreneurs do not operate in a vacuum to create wealth but respond to opportunities that come in two basic forms, innovation and arbitrage. Innovative (Schumpeterian) opportunities mainly relate to creating new combinations of goods and services, raw materials, and production methods (also known as ends, means, and means-ends frameworks[1]) that result in more efficiently using certain resources. Compared to existing uses of these resources, the benefits of pursuing new combinations outweigh the costs (Eckhardt & Shane, 2003; Schumpeter, 1934). This new efficiency is then converted into economic benefits that the creative entrepreneur appropriates as entrepreneurial rents (Alvarez & Barney, 2004). Arbitrage (Kirznerian) opportunities, in contrast, exist because markets are inefficient and do not adjust instantaneously to changing realities (Kirzner, 2008). As a result, resources are often priced differently in different markets, and those who notice discrepancies can promptly exploit them. Thus, while innovative entrepreneurs generate profit through new resource combinations, alert arbitrageurs profit by removing market inefficiencies. Although the benefits of pursuing arbitrage opportunities are finite, the risks involved are typically lower. As a result, many entrepreneurs concentrate on arbitrage opportunities rather than on attempting to innovate (Rivkin, 2001).

The entrepreneurship literature conceptually recognizes both innovative (sometimes explicitly called entrepreneurial) and arbitrage (sometimes called optimizing or trivial)

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opportunities. Yet, research to date has not offered an acceptable operationalization of arbitrage opportunities and has instead focused on Schumpeterian innovation. Currently, there is no established way to assess the number of arbitrage opportunities a company might exploit within a certain industry.

Conceptually, such operationalization should solve two problems. First, it should identify the technological frontier by locating benchmark firms and modeling their efficiency. Second, it should quantify discrepancies between the firms' resource allocation and the benchmark. Interestingly, a group of techniques exists that are uniquely qualified for this task. Although the management and innovation literatures have used these techniques in the past (Dutta, Narasimhan, & Rajiv, 2005; Thursby & Thursby, 2002), they have never been employed to quantify arbitrage opportunities. We believe that using these techniques will be of significant value to the field of entrepreneurship.

In this article, we outline the basic approaches that could be used for this task and review previously used techniques found in extant research. Importantly, we explicate the features of the most widely used techniques that render them less desirable for quantifying arbitrage opportunities. We also suggest an alternative technique—minimum performance inefficiency (MPI)—that resolves the challenges inherent to other approaches. We demonstrate the use and benefits of MPI using a previously validated data set with known properties and illustrate its application using secondary data on the publishing industry from 1998 to 2003. Although our technique allows analysis of opportunities at multiple levels, we focus on the industry level.

Identifying and Measuring Arbitrage Opportunities

From Innovative to Arbitrage Opportunities

Industries differ with respect to the amount of entrepreneurial activity they generate and sustain. Because entrepreneurship implies the nexus of entrepreneurs and opportunities (Shane & Venkataraman, 2000), it is reasonable to assume that the number of opportunities to which entrepreneurs respond differs among industries. Extant research has acknowledged this reality and has developed accepted means to measure the innovative opportunities available in different industries. These measures include perceived opportunities for product innovation, technological innovation, R&D spending, industry technological breakthroughs (Zahra, 1996), and average industry R&D divided by average industry sales (Tihanyi, Johnson, Hoskisson, & Hitt, 2003).

Innovation, however, is not always necessary for entrepreneurial rents to exist. Because markets are imperfect and resource owners have bounded rationality, certain changes may render existing resource pricing ineffective. Such changes may be attributed to general forces or external events—such as military conflicts, political instability, or changes in consumer tastes—but may also reflect recent discovery or creation of hitherto unknown products, markets, or other advances within a particular industry (Kirzner, 2008). Regardless, in many industries opportunities can be found due to already existing but as yet widely unnoticed changes that may be exploited by alert arbitrageurs.

To benefit from arbitrage opportunities, entrepreneurs must employ their resources in a manner similar to the most successful companies in their industry.[2] Often, significant improvements in deploying resources efficiently could result from a novel means-ends framework discovered by an original innovator (Eckhardt & Shane, 2003), which alert arbitrageurs could imitate.[3] Even a relatively insignificant innovation in a low-tech industry such as residential landscaping may disturb market balance and generate opportunities for rent extraction by imitators. For example, a small start-up company called ChemLawn of Troy, Ohio (now known as TruGreen) pioneered a novel concept of liquid lawn care in 1968. It had discovered a cost-efficient way to uniformly apply fertilizer to customers' lawns. By acquiring the basic ingredients of commercial lawn food, mixing them, and applying the mixture for customers in a novel way, ChemLawn turned into a powerful competitor for sellers of higher priced, premixed products produced by companies such as O.M. Scott and Ortho. This innovation has led to enormous company growth (ChemLawn's sales exceeded U.S.$300 million in 1985) but also opened arbitrage opportunities for lawn care businesses who later imitated the concept of liquid lawn care (Nayak & Ketteringham, 1986). Rivkin (2001) provides another illustration of this concept by discussing White Castle and its imitators.

On Quantifying Opportunities

With this article, we suggest a group of models that are uniquely appropriate for quantifying arbitrage opportunities. The models define the technological frontier in the industry and then measure how far inefficient firms are from the frontier. Arbitrage opportunities imply optimization under already existing (but not yet necessarily standard) means-ends frameworks. Therefore, to evaluate the magnitude of arbitrage opportunities available to a firm, one needs to assess the effectiveness with which the firm combines its resources against a benchmark. In this case, the benchmark is the industry's leaders—that is, those who are best at combining resources (inputs) to produce certain outputs. This distance from the industry's best-known way to combine resources thus represents (or should be proportional to or at least monotonically related to) the room available for optimization. For this method to be effective, narrowly defined industry membership is important for several reasons. First, a narrow definition ensures that inputs and outputs are comparable across different firms. Second, narrowly defining the industry is important because similar resources (e.g., human or technological resources) may yield dramatically different returns in different industries (e.g., biotechnology vs. residential landscaping).

For firms that define the industry's best technologies, arbitrage opportunities would only be available if a general change—such as consumer preferences—occurs. Without this kind of change, there is no better use for resources that firms could possibly imitate to earn higher entrepreneurial profit. Less efficient firms, however, can imitate their industry's leaders; innovation is neither the only nor the best way for them to improve efficiency. Imitation allows less efficient firms to learn from industry leaders and move closer to the frontier without facing the uncertainty associated with innovation. Thus, such companies will be motivated to imitate (move toward the frontier) until they reach the level of efficiency similar to that of industry leaders. Because innovation never stops, this process never concludes. An industry's technological frontier becomes somewhat of a horizon for inefficient firms, because the frontier continues to move away as firms approach it.

Review and Critique of Existing Techniques

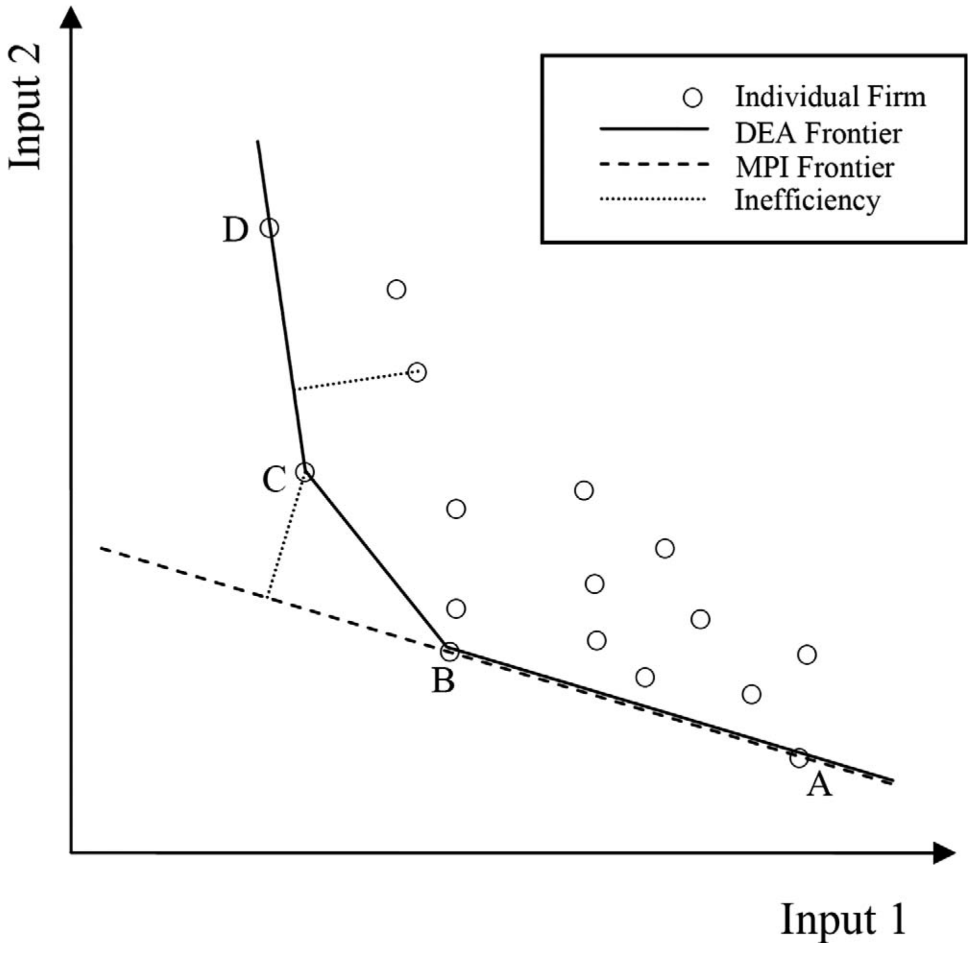
Techniques capable of measuring arbitrage opportunities are collectively known as "efficiency evaluation techniques." According to Färe, Grosskopf, and Russell (1998), these techniques can be classified into four main categories: (a) parametric deterministic (Aigner-Chu); (b) parametric stochastic (stochastic frontier estimation or SFE); (c) nonparametric deterministic (data envelopment analysis or DEA); and (d) nonparametric stochastic techniques (stochastic DEA or SDEA). Aigner-Chu models (Aigner, Lovel, & Schmidt, 1976; Førsund, Lovell, & Schmidt, 1980) constitute a class of frontier estimation models that have maximum likelihood properties when specific distribution assumptions govern the errors. This class has not been used widely because such distribution assumptions are rarely found to hold. SDEA involves a number of judgmentally assigned parameters. As such, it may be regarded as a kind of exploratory tool. Of the remaining approaches, DEA is the most commonly used, followed by SFE. Accordingly, we consider DEA and SFE in more detail, with particular attention to the underlying logic of DEA as the most popular approach to evaluating efficiency.

DEA models (see e.g., Charnes, Cooper, Lewin, & Seiford, 1994, for detail and mathematical formulation) arose from studying the efficiency of so-called input-output units such as firms that combine their resources (inputs) to produce different outputs. For simplicity in this article, we consider labor and capital as the two input variables and sales as the only output variable. DEA models are based on ratios of weighted sums of outputs and inputs. Output weights are analogous to prices, whereas input weights are similar to costs. Thus, in essence, the DEA measure resembles a ratio of output value to input value. Importantly, the DEA approach is firm-specific: it finds weight values that maximize each firm's efficiency ratio, regardless of whether those weights (prices) are consistent with or favorable to other firms. In reality, however, prices are often set for the entire industry by market mechanisms such that even somewhat heterogeneous resources such as skilled labor are priced homogenously. Thus, the fact that DEA permits each firm to have its own set of input costs and output prices rather than consensus (market-based) weights is problematic and artificially inflates many firms' efficiencies. It follows that a firm may be declared fully efficient using its own DEA weights but not be fully efficient using the weights of another firm. This problem may be viewed as a kind of rubber yardstick or as Troutt, Ehie, and Brandyberry (2007) termed it, the "everything is beautiful in its own way" problem of DEA.[4]

Another view of this issue uses a second interpretation of the DEA weights as quantities that describe the tangent lines to the efficient frontier. Figure 1 illustrates a case of four efficient firms on a frontier. Weights that make firms A and B efficient determine the line segment passing through points A and B and hence the tangent line of which this segment is a portion. We can see that firms C and D would not be efficient using this tangent line. In short, the DEA model appears too generous in allowing each firm to select favorable weights rather than applying consensus weights equitably to all firms in the industry (such as industry-specific labor costs).

SFE, as discussed in Banker, Datar, and Rajan (1987), assumes a parametric frontier and models data observations as departures or errors from the frontier, similar to errors from a regression function. Because errors in SFE are combinations of a firm's inefficiency and a general random disturbance, however, the choice of numerous distributional assumptions

Figure 1
Representation of Data Envelopment Analysis (DEA) and Minimum Performance Inefficiency (MPI) Frontiers



Note: Illustrated are the amounts of input 1 and input 2 (e.g., capital and labor) used by firms A, B, C, and D to produce a certain amount of a particular output (e.g., sales).

for each of the two error components is very difficult and leads to specification problems. This may necessitate very large data sets to accurately estimate the parameters.

Using MPI Estimation to Gauge Arbitrage Opportunities

Suggested Approach: MPI Estimation

With the foregoing DEA background, we can now describe this article's proposed models. As with DEA, these models begin with ratios of weighted sums of outputs and inputs. Thus, for the MPI formulation, the ratio of the weighted sum of outputs to the weighted sum of inputs is considered for each firm. Weights are not free to vary from unit (e.g., firms, entrepreneurs) to unit as in DEA, however. Instead, the MPI model seeks consensus weights so that all units are held to the same standard of efficiency score calculation.

To determine such consensus weight sets, two considerations are used. First, we assume that there is an acceptable set of most appropriate weights for inputs and outputs that should apply to all firms. Specifically, such weights should be those prices and costs that managers would judge appropriate in a relevant market for outputs and inputs.

Second, a principle is needed to estimate appropriate common weights. We use the MPI principle. This approach has been developed in Troutt (1995) and Troutt, Gribbin, Shanker, and Zhang (2000) and is discussed further in Troutt, Pang, and Hou (2004). It is reasoned that in trying to exploit arbitrage opportunities, each firm wishes to minimize inefficiency. Thus, on average, all firms attempt to minimize individual inefficiencies in their actions and decisions. It therefore follows that an industry's firms as a group attempt to minimize their average, or equivalently, their total inefficiency. We therefore estimate the weights as those that minimize the total performance inefficiencies (MPI) of the firms. Alternatively, we could use the maximum performance efficiency (MPE) formulation, where we estimate the weights as those that maximize total of the firm efficiencies.

The choice of whether to use the MPE or MPI formulation can be based on computational convenience with respect to the numbers of inputs and outputs, as will be seen in our application to the illustrative data below. The case of one output, as in our data illustration, lends itself to MPI and simplifies the calculations. In the MPI case, constraints similar to those in DEA are used, namely (a) the ratio for each firm will be less than or equal to unity, and (b) all weights are nonnegative. In terms of the Färe et al. (1998) classification scheme, MPI may be regarded as deterministic because separate frontier error and inefficiency error distributions are not required to be assumed. Furthermore, the MPI method is essentially a parametric method because the input weights of the model determine a linear frontier.

To summarize, the MPI formulation solves a mathematical programming problem that minimizes the sum of inefficiency ratios (weighted sums of inputs divided by weighted sums of outputs) subject to the constraints that inefficiency ratios are greater than or equal to unity for all firms.

Comparison With DEA

DEA uses a maximum objective for each firm's efficiency ratio (or minimum for inefficiency formulations) as a mathematical way to determine the frontier. This is not the same as assuming that all firms seek to maximize their performance based on consensus weights, as with the MPI approach. This has been called the performance improvement motive (Troutt et al., 2004). The maximization or minimization operations of DEA are motivated by geometric relationships in finding the tangents to the efficient frontiers. In contrast, in the MPI approach the minimization operations arise as attempts to reproduce firms' and their managers' presumed behavior. Consider the performances of the firms that are not on the frontier in Figure 1 (arbitrageurs). There is a clear indication in this case that most firms are clustering near the frontier in the direction of the indicated tangent. We interpret this to suggest that consensus is indicated by emphasizing that particular direction of approach to the frontier. As noted, performance improvements are reflected in entrepreneurial profits. DEA and other technical efficiency methods, however, do not necessarily make such an assumption. This assumption, however, is implicit in our conceptual development.

Figure 1 also suggests that the MPI method gives maximal performance to fewer firms than does DEA. That is, fewer firms will be considered fully efficient. This is a result of using consensus weights for all firms. A firm declared efficient in the MPI approach will also be DEA efficient. However, the opposite does not hold: many DEA-efficient firms will fail to be MPI efficient. By declaring those firms efficient, DEA fails to indicate arbitrage opportunities that are, in fact, present for them. Thus, the MPI method may be considered a more stringent efficiency measure than DEA. This may enhance researchers' ability to reveal arbitrage opportunities where methods such as DEA would identify none.[5]

Validating MPI Compared to DEA

This more stringent nature of the MPI model is further illustrated with Table 1, which is based on the well-known test data set proposed by Sherman (1981) and discussed in Bowlin, Charnes, Cooper, and Sherman (1985). This data set gives the inputs and outputs of a set of 15 hypothetical hospitals, each having three inputs and three outputs. Sherman constructed the data set so that hospitals H1–H7 were intended to be fully efficient, whereas hospitals H8–H15 had inefficiencies of various degrees.[6]

Comparing the efficiency scores computed by the general MPI model with the efficiency scores obtained by the DEA model suggests that the MPI estimates are superior to those based on DEA. As shown, hospitals H10, H11, H13, and H15 were found to be relatively inefficient by the MPI model. Only hospital H15 was found to be relatively inefficient by DEA, however. We regard this as indicating that DEA is not sufficiently sensitive to measure efficiency differences. In contrast, the MPI technique is more sensitive to the presence of inefficiency than is DEA; in other words, it is more difficult to be efficient under the MPI approach than the DEA approach. It can also be seen that the MPI method yielded fewer hospitals misclassified as efficient. In particular, MPI produced four misclassified hospitals, whereas DEA yielded seven.

Illustration With Actual Data

Finally, to illustrate the use of the MPI estimation technique to measure arbitrage opportunities, we refer to secondary data from 1998–2003 related to the publishing industry (including newspaper, periodical, book, directory and mailing list, and other publishers [NAICS codes 51111, 51112, 51113, 51114, and 51119]). Using the Microsoft Excel-based MPI-solver we developed, we calculated the MPI estimates. This tool is available to researchers at http://mis.kent.edu/Members/abrandyb/mpi/mpi-template.

For each firm, we used Compustat to obtain data on total assets, number of employees, and sales. Total assets and number of employees were used as model inputs and sales were used as the model output.[7] After removing firms with missing values for any of the variables in any

Table 1
MPI Versus DEA Using Sherman's Hospital Data

		Inputs			Outputs				
	Hospital Unit	Full-Time employment	Bed Days	Supply U.S.$[a]	Teaching Units	Regular Patients[a]	Severe Patients[a]	MPI Efficient?	DEA Efficient?
Constructed as efficient	H1	23.5	41,050	130	50	3	2	Yes	Yes
	H2	24.5	43,160	140	50	2	3	Yes	Yes
	H3	26	43,160	150	100	2	3	Yes	Yes
	H4	25	41,050	140	100	3	2	Yes	Yes
	H5	28.5	50,530	160	50	3	3	Yes	Yes
	H6	36	62,105	210	100	2	5	Yes	Yes
	H7	51.5	92,630	270	50	10	2	Yes	Yes
Constructed as inefficient	H8	25	49,475	140	100	3	2	Yes	Yes
	H9	24.5	43,160	165	50	2	3	Yes	Yes
	H10	77	92,630	340	100	10	2	No	Yes
	H11	44.5	65,260	265	50	5	3	No	Yes
	H12	30	60,000	170	100	3	3	Yes	Yes
	H13	43.5	81,110	245	50	4	5	No	Yes
	H14	30	60,000	170	100	3	3	Yes	Yes
	H15	26.5	47,370	160	50	3	2	No	No

[a] In 1,000s.

given year, we retained information on 38 firms. Because publishing is a highly concentrated industry, we believe that our sample is representative of the prevailing practices in the industry.

Table 2 lists our arbitrage opportunities estimates (AOEs)—the inefficiency measure—for the industry firms. Estimates of 1.000 indicate perfect efficiency (relative to the firms used in the computations) and associated lack of arbitrage opportunities. For such firms, only innovative opportunities could be used to further increase efficiency when combining these inputs to produce this output, unless an external change occurs that necessitates re-pricing of the resources that the firms use or their products. AOEs above 1.000 indicate imperfect efficiency and presence of arbitrage opportunities.

As shown in Table 2, two firms are considered efficient in every year, and we see a gradual change in the firms that determine the industry frontier from year to year. One of the firms (Reader's Digest) was at the industry forefront 4 of the 5 years. Two firms (News Communications and Track Data Corp.) were each defining the frontier during a three-year period. Finally, one firm (Thomas Nelson Inc.) was the industry's benchmark for 2 of the 6 years. If our earlier conjectures are correct, these firms should turn primarily to innovation rather than arbitrage opportunities to pursue entrepreneurial rents, while for their less efficient counterparts, arbitrage would suffice.

Conclusions

Our study's contribution need to be viewed in light of its limitations. The chief challenge of our approach is its implicit assumption of comparability of production functions used by

Table 2
Arbitrage Opportunity Estimates (Inefficiency Scores) in the Publishing Industry, 1998–2003

Company Name	Ticker	1998	1999	2000	2001	2002	2003
American Greetings	AM	2.854	2.241	3.041	2.400	2.813	2.316
Belo Corp.	BLC	3.911	4.000	3.269	3.897	3.077	2.906
Cadmus Communications Corp.	CDMS	1.660	2.001	1.794	1.406	1.455	1.124
Dag Media Inc.	DAGM	2.546	3.834	2.349	3.040	2.446	1.791
Daily Journal Corp.	DJCO	2.008	1.664	2.254	1.473	1.515	1.344
Dow Jones & Co Inc.	DJ	1.278	1.214	1.154	1.253	1.188	1.162
Gannett Co.	GCI	2.534	2.700	3.347	3.229	2.903	2.755
Gemstar-TV Guide Intl Inc.	GMST	2.225	2.697	16.881	9.410	2.325	1.698
Hollinger Intl Inc.	HLR	2.678	2.534	2.008	2.589	2.699	2.089
Journal Communications Inc.	JRN	1.895	1.559	2.027	1.679	1.643	1.441
Journal Register Co.	JRC	3.256	2.488	2.687	3.148	2.829	2.509
Knight-Ridder Inc.	KRI	2.506	2.057	2.290	2.327	2.071	1.825
Lee Enterprises Inc.	LEE	2.797	2.245	3.642	3.753	3.999	2.889
Liberty Group Publishing Inc.	LZPI	7.000	4.908	5.497	4.637	4.286	3.881
Mcclatchy Co.	MNI	4.101	3.159	3.151	3.125	2.653	2.293
Mcgraw-Hill Companies	MHP	1.767	1.568	1.749	1.694	1.385	1.356
Media General	MEG	3.497	4.443	4.726	4.730	3.708	3.491
Meredith Corp.	MDP	1.681	1.979	1.753	1.950	1.743	1.507
Monarch Services Inc.	MAHI	2.951	3.372	3.165	2.970	2.358	2.329
Thomas Nelson Inc.	TNM	1.716	1.688	1.537	1.325	1.000	1.000
New York Times Co.	NYT	2.015	1.702	1.630	1.752	1.562	1.454
News Communications	NCOM	1.898	1.260	1.788	1.000	1.000	1.000
Pearson plc	PSO	3.476	2.374	2.974	2.755	1.987	1.863
Penton Media Inc.	3PTON	3.381	3.839	2.665	2.723	2.177	1.842
Plato Learning Inc.	TUTR	1.461	1.561	1.806	2.988	2.599	2.473
Primedia Inc.	PRM	3.092	2.319	2.220	2.298	1.471	1.466
Private Media Group Inc.	PRVT	2.047	2.249	2.203	2.219	2.045	2.013
Pulitzer Inc.	PTZ	2.551	3.652	4.380	4.709	4.008	3.743
Reader's Digest Association, Inc.	RDA	1.000	1.000	1.000	1.000	1.355	1.188
Scholastic Corp.	SCHL	1.555	1.190	1.321	1.475	1.441	1.047
Touchstone Applied Sci Association, Inc.	3TASA	3.654	2.340	3.009	2.055	1.698	1.106
Track Data Corp.	TRAC	1.000	1.000	1.000	1.859	1.140	2.108
Tribune Co.	TRB	3.127	3.894	3.874	3.934	3.068	2.863
Trudy Corp.	3TRDY	1.381	1.364	2.401	1.400	1.243	1.042
United Business Media	UNEWY	1.809	1.972	2.787	3.420	2.425	2.268
Washington Post	WPO	2.227	2.066	2.006	2.259	1.822	1.707
Wiley (John) & Sons	JW.A	1.790	1.467	1.573	1.872	1.498	1.355
Wolters Kluwer nv	WTKWY	2.838	2.760	2.638	2.601	2.063	1.794

the firms. If the production functions that firms use are drastically different, their resources may also differ such that our consensus weights condition may lose its importance. If this is the case, standard DEA-based models may become an alternative in that they provide for firm-specific resource costs and output prices. This may be particularly true when opportunities are assessed in a cross-country and not within-industry context, and countries rather than firms become a unit of analysis. Furthermore, the problem of a market's homogenous pricing of heterogeneous resources always exists. Resources employed by competitor firms with nearly identical products (e.g., Pepsi and Coke) are not truly identical even though such identity is implicitly assumed when resource prices are taken into consideration for estimating the frontier. This clearly may become a limitation. Future research should explore the boundary conditions for applying these techniques in the context of arbitrage opportunities.

Despite this limitation, one very practical use of the estimates of opportunities obtained from efficiency evaluation techniques is that they can be used in a second-stage regression analysis as either independent or dependent variables (Färe et al., 1998). For example, arbitrage opportunities may be considered an alternative driver of entrepreneurial behavior and strategic choices in addition to innovative opportunities. Similarly, inefficiency scores might be of interest as dependent variables in models predicting factors that account for persisting or declining arbitrage opportunities over time. In fact, the surprising persistence of arbitrage opportunities available for the firms in our sample, despite the fact that such opportunities are obviously short-lived, may suggest path dependencies. This certainly calls for empirical investigation.

Although exploiting innovative and arbitrage opportunities is key to understanding entrepreneurial dynamics, current entrepreneurship research has not yet provided universally accepted operationalizations of arbitrage opportunities. This article presents a technique that may be used for this purpose. The technique calculates arbitrage opportunities by quantifying the possibilities a firm has to improve the efficiency with which it combines resources to an optimal level under the current means-ends framework. We believe this technique is an important contribution to entrepreneurship research and hope that it will encourage empirical studies that consider opportunities in their entirety.

Notes

1. In the entrepreneurship literature, "new ends" refers to new products and services (e.g., the introduction of Crocs shoes in 2002); "new means" refers to new inputs used to make known and widespread products and services (e.g., formulation of new water-borne coatings and other materials that are nonpolluting and nontoxic to be used by paint companies); and "new means-ends frameworks" refers to new methods of production (e.g., a recent discovery by UCLA researchers of a new method to produce biofuels that could lead to mass production of these biofuels).

2. Although Kirzner (1997, 2008) concentrates on how much money current arbitrageurs have earned, we focus on how much money could have been earned by would-be arbitrageurs. Hence, our attention is on arbitrage opportunities and not de facto arbitrage. We also extend the framework to collective entrepreneurs (firms) and not just individuals.

3. Although this is not a concern in low-tech industries or industries with a weak appropriability regime, in high-tech industries with a tight appropriability regime, it may not be possible to perfectly imitate the benchmarked company's innovation. Thus, even though arbitrage opportunities may be present in the latter industries, they may not be available for immediate exploitation. Perhaps future research will explore whether arbitrage opportunities are more persistent in such industries.

4. Under DEA, firms not on the frontier will be inefficient for any set of weights.

5. A mathematical explanation of the differences between the methods is available upon request.

6. Sherman (1981) contains detailed information on how the inefficiencies were modeled.

7. The technique allows for multiple inputs and multiple outputs. Our example is simplified; the purpose is to illustrate using the technique. Our estimates of arbitrage opportunities may change if other factors are

considered inputs or outputs. Furthermore, we believe that selecting inputs and outputs should be dictated by the theory used to derive hypothesized relationships.

References

Aigner, D. J., Lovel, C. A. K., & Schmidt, P. (1976). Formulation and estimation of stochastic frontier production function models. *The Rand Series Working Paper No. P-5649*. Retrieved December 10, 2008, from http://www.rand.org/pubs/papers/2008/P5649.pdf

Alvarez, S. A., & Barney, J. B. (2004). Organizing rent generation and appropriation: Toward a theory of the entrepreneurial firm. *Journal of Business Venturing*, *19*, 621-635.

Banker, R. S., Datar, S., & Rajan, M. (1987). Measurement of productivity improvements: An empirical analysis. *Journal of Accounting, Auditing and Finance*, *2*, 319-347.

Bowlin, W. F., Charnes, A., Cooper, W. W., & Sherman, H. D. (1985). Data envelopment analysis and regression approaches to efficiency estimation and evaluation. *Annals of Operations Research*, *2*, 113-138.

Charnes, A., Cooper, W. W., Lewin, A., & Seiford, L. M. (1994). *Data envelopment analysis: Theory, methodology and applications.* Boston: Kluwer Academic Publishers.

Dutta, S., Narasimhan, O., & Rajiv, S. (2005). Conceptualizing and measuring capabilities: Methodology and empirical application. *Strategic Management Journal*, *26*, 277-285.

Eckhardt, J. T., & Shane, S. A. (2003). Opportunities and entrepreneurship. *Journal of Management*, *29*, 333-349.

Färe, R., Grosskopf, S., & Russell, R. R. (Eds.). (1998). *Index numbers: Essays in honor of Sten Malmquist*. Norwell, MA: Kluwer Academic Publishers.

Førsund, F. R., Lovell, C. A. K., & Schmidt, P. (1980). A survey of frontier production functions and of their relationship to efficiency measurement. *Journal of Econometrics*, *13*, 5-25.

Kirzner, I. (1997). Entrepreneurial discovery and the competitive market process: An Austrian approach. *Journal of Economic Literature*, *35*, 60-85.

Kirzner, I. (2008). The alert and creative entrepreneur: A clarification. IFN Working Paper No. 760. Retrieved December 10, 2008, from http://ssrn.com/abstract=1224842

Nayak, P., & Ketteringham, J. (1986). *Breakthroughs*! New York: Rawson Associates.

Rivkin, J. W. (2001). Reproducing knowledge: Replication without imitation at moderate complexity. *Organization Science*, *12*, 274-293.

Schumpeter, J. A. (1934). *The theory of economic development.* Cambridge, MA: Harvard University Press.

Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of Management Review*, *25*, 217-226.

Sherman, H. D. (1981). *Measurement of hospital technical efficiency: A comparative evaluation of data envelopment analysis and other approaches for locating inefficiency in health care organizations*. Unpublished doctoral dissertation, Harvard University.

Thursby, J. G., & Thursby, M. C. (2002). Who is selling the ivory tower? Sources of growth in university licensing. *Management Science*, *48*, 90-104.

Tihanyi, L., Johnson, R. A., Hoskisson, R. E., & Hitt, M. A. (2003). Institutional ownership differences and international diversification: The effects of boards of directors and technological opportunity. *Academy of Management Journal*, *46*, 195-211.

Troutt, M. D. (1995). A maximum decisional efficiency estimation principle. *Management Science*, *41*, 76-82.

Troutt, M. D., Gribbin, D. W., Shanker, M., & Zhang, A. (2000). Cost efficiency benchmarking for operational units with multiple cost drivers. *Decision Sciences*, *31*, 813-832.

Troutt, M. D., Ehie, I. C., & Brandyberry, A. A. (2007). Maximally productive input-output units. *European Journal of Operational Research*, *178*, 359-373.

Troutt, M. D., Pang, W. K., & Hou, S. H. (2004). *Vertical density representation and its applications.* Singapore: World Scientific Publishing Co. Pte. Ltd.

Zahra, S. A. (1996). Governance, ownership, and corporate entrepreneurship: The moderating impact of industry technological opportunities. *Academy of Management Journal*, *39*, 1713-1735.

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