Human Resource Management's Effects on Firm-Level Relative Efficiency

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Using stochastic frontier production functions methodology with data from 1579 private-sector establishments, we demonstrate that HR practices are significantly associated with differences in relative firm-level efficiency. Supplemental analysis implies that this efficiency analysis is substantively different than the common approach to evaluating HRM's relationships with firm-level labor productivity. The results suggest that HR practices' contributions to relative firm-level efficiency are an important but heretofore overlooked factor in the relationship between HRM and firm performance.

Introduction

A FAVORITE DEPENDENT VARIABLE IN THE LITERATURE ON HUMAN RESOURCE MANAGEment (HRM) and firm performance is firm-level labor productivity. There is an established argument that this outcome is more proximate to HRM practices than other common measures of firm-level performance such as market share or stock price (e.g., Arthur 1994; Colakoglu, Lepak, and Hong 2006; Dyer 1984; Dyer and Reeves 1995; Rogers and Wright 1998). However, there are drawbacks to the ways in which firm-level labor productivity has been operationalized in most of the current literature. One common shortcoming is that many papers in this stream of research employ firm-level labor productivity measures that do not account for firms' labor costs, and conceptually, labor costs should anchor any estimates of productivity. Simply accounting for labor costs, though, does not necessarily create an accurate picture of firm-level labor productivity in a broad sample of firms. This is because the usual approach employed by HRM researchers evaluates firm-level labor productivity with respect to a specific configuration of HRM variables—a particular HRM

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production function, in essence. Explanations of firm-level labor productivity based on such analyses can be substantially incomplete when that HRM production function is not uniformly relevant across a diverse sample of firms.

However, the methodology that we employ in this paper can identify the effects of HR practices on firm performance while accommodating HRM configurations that are idiosyncratic across firms. This allows us to investigate HR practices' effects on firm performance without reference to a specific HRM production function. We also have general cost data for firms' labor and capital production inputs. As we demonstrate, these advantages generate an alternate view of the relationships between HRM and firm performance that complements what can be learned from the usual approach to this question in the extant literature.

Problems with the Usual Approach to HRM and Firm-Level Productivity

The Problem of Omitted Labor Costs. As we suggested above, the typical approach to evaluating HRM's effects on firm-level labor productivity exhibits two major drawbacks. Let us first consider the issue of labor costs. Researchers on HRM and firm performance have often employed sales per employee as a measure of firm-level labor productivity (e.g., Datta, Guthrie, and Wright 2005; Guthrie 2001; Huselid 1995; Koch and McGrath 1996; Sun, Aryee, and Law 2007). This measure has its strengths. First, total sales is an outcome that is more proximate to HRM practices than are accounting measures of firm performance. Moreover, total sales is a relatively straightforward measure of firm output compared with accounting performance measures, which can vary across firms depending on their treatment of various accounting issues. This may be particularly true in diverse samples where firms have notably different approaches to creating value. Furthermore, dividing sales revenue by a firm's number of employees scales output to firm size, which is an important consideration because firm size and sales revenue are positively correlated. Thus, sales per employee is a broad measure of how successful firms are at generating revenue. When sales per employee is estimated conditional on such factors as industry, capital intensity, ownership structure, unionization, and the like, it becomes comparable across a population of firms.

But sales per employee is only labor productivity in the broadest sense of the term, that is, in that the size of a firm's workforce is the denominator in a measure of firm output. The same logic applies equally well to alternative measures such as market share per employee, patents per employee, and the like. As labor productivity, however, such measures are incomplete. Productivity has

traditionally been defined as the ratio of a firm's labor inputs to its outputs, or, in other words, the efficiency with which a firm converts resources into salable goods and services. Concern for both outputs and inputs is crucial. Firms with the same level of sales per employee, for instance, may have very different labor productivities if they differ in the costs of the labor inputs required to produce those sales.

Accordingly, a number of observers have called for studies on the relationship between HRM and firm-level labor productivity to include labor costs as well as estimates of the benefits firms derive from their sets of HR practices (e.g., Barney and Wright 1998; Cappelli and Neumark 2001; Macky and Boxall 2007). These costs can significantly modify the inferences that researchers draw from their analyses, which have generally described positive relationships between HRM and firm-level labor productivity (e.g., Combs et al. 2006). For example, Cappelli and Neumark (2001) found that increases in firm performance associated with high commitment HR practices were counterbalanced by corresponding increases in employee compensation. Consequently, the HR practices studied by Cappelli and Neumark led to higher output per worker but not necessarily to greater firm-level productivity because returns to the firm were not meaningfully higher. Similarly, Way (2002) could not find a significant relationship between his HRM system measure and firm-level labor productivity when labor productivity was assessed as total sales divided by total labor costs. Additionally, Kim (2005) demonstrated that transaction and implementation costs substantially reduced the positive estimated impact of a gainsharing program. In short, evidence suggests that HRM's effects on firms' revenues can be different than HRM's effects on firms' *net* revenues, making the latter type of productivity estimations preferable.

The Problem of Ties to Specific HRM Production Functions. Yet, accounting for costs may not be sufficient by itself to generate a complete picture of HRM and firm-level labor productivity. Consider a typical HRM/firm-level labor productivity model utilizing a set of HR practices in a regression. The particular HR practices that a researcher chooses to employ and the ways that she relates those practices to each other in the analysis are her theoretic specification of an ''HRM production function'' regarding the dependent variable (cf. Zyphur 2009). Inferences about firm-level labor productivity from that regression are therefore bound to that HRM production function and dependent variable. Consequently, this approach is better at evaluating a particular configuration of HR practices vis-à-vis a specific firm-level outcome than at capturing HRM's overall effects on that firm-level outcome.

If a researcher constructs an additive index containing HR practice variables measuring training, selection, performance appraisal, and incentive compensation,

for example, the analysis will evaluate the strength of that particular HR index's relationship with the dependent variable for firms in the sample. Firm-level labor productivity that is not attributable to this HR index (for example, because some sample firms effectively utilize HR practices that are not part of the index) or that is not related to the control variables becomes part of the regression's residual variance. Moreover, if an additive approach to configuring these HR practices does not suitably reflect the HR practices' interrelationships with respect to the dependent variable, the regression can misrepresent the studied HR practices' collective effects (Chadwick 2010). In other words, the insight gained from this analysis depends on the salience of the specified HR production function in the sample.

Consequently, this approach can also yield significantly incomplete explanations of firm-level labor productivity in data containing firms with widely differing approaches to competition because a single HRM production function may not be uniformly relevant across the sample. One solution to this problem is to define samples narrowly enough so that it is possible for a single strategy and its matching HRM production function to be optimal for all sample firms. MacDuffie (1995), for example, found that a single theoretically defined HRM system was well matched to lean production in automobile assembly. However, even where this is possible, defining a sample so narrowly can significantly limit generalizability and statistical power.

Fortunately, the data that we utilize in this paper can speak to the labor cost issue, while the methodology that we employ addresses the HRM production function concern, allowing us to more accurately estimate HRM's overall effects on firm-level labor productivity irrespective of a specific HRM production function. As this paper demonstrates, this approach provides an insightful complement to the usual approach to estimating firm-level labor productivity. To hypothesize about HR practices' influence on firm-level labor productivity in the next section of the paper, we begin with the general concept of efficiency.

HRM and Efficiency in Theory

We start with efficiency because labor productivity is a form of efficiency. Efficiency concerns a firm's ability to combine production inputs to create the products that it sells to customers. Conceptually, firm-level efficiency is higher if a set of HR practices increases firm performance more than the practices' effects on labor costs (i.e., compensation, benefits, etc.). If a set of HR practices brings in returns (through increases in workers' effectiveness) below their effects on labor costs, it is not efficient. On the other hand, returns to the firm

above a set of HR practices' effects on labor costs increase firm efficiency and at some point may also signal competitive advantage accruing to the firm through that set of HR practices. Thus, changes in compensation practices such as gainsharing and pay for skill that are scaled to increases in workers' contributions to the firm are unlikely to change firm-level efficiency either positively or negatively because the ratios of firms' costs to benefits for these practices remain constant across different degrees of worker effectiveness.

In contrast, if the biggest effect of an HR practice on labor productivity occurs when the practice is adopted (i.e., non-adopters pay a steep price in lower productivity), then a variable measuring that practice could generate a significant relationship with relative firm-level efficiency even if fairly large proportions of firms in a sample employ the practice. It is possible, for example, that some fairly straightforward HR practices that are important to firm functioning may not be adopted by some firms for institutional reasons (e.g., firm cultures, path dependence). Because these practices are relatively easy to understand and imitate, they do not contribute to competitive advantage, but rather serve as baseline terms of competition (or what Boxall and Purcell [2000] call ''table stakes''), which all comparable firms should implement to achieve competitive parity. With such HR practices, pursuing firm-level efficiency is mostly about avoiding competitive *disadvantage* by not omitting important baseline practices.

In either event, this paper's methodology is well fitted to these notions of efficiency, although it is largely new to the HRM and firm performance literature. The reference that anchors our estimation of firm-level labor productivity is sample firms' efficiency relative to each other, an approach that allows our analysis to remain agnostic about the specific configurations of HR practices (or HRM production function) that firms employ. Firm-level relative efficiency encompasses labor productivity when it is estimated conditional on a firm's labor input costs. We operationalize HRM's effects on firm-level labor productivity as the variance in overall firm-level relative efficiency, conditional on labor costs, that is attributable to firms' sets of HR practices (we explain this methodology in detail below).

Along with other classes of firm resources such as technology, reputational capital, organizational capital, financial capital, and physical resources, human capital is essential to firm functioning (Chadwick and Dabu 2009). Relative firm-level efficiency is a summary of the quality of firm functioning. Therefore, it is likely that heterogeneity in firms' pools of human capital helps to determine differences in firm-level relative efficiency. Indeed, Lopez-Cabrales, Valle, and Herrero (2006) recently linked heterogeneity in core employees' human capital with differences in relative firm-level relative efficiency in a sample of Spanish firms. Lopez-Cabrales et al.'s study did not test, however,

the relationship between HR practices and firm-level relative efficiency. Nevertheless, extensive empirical and theoretic arguments in the HRM literature establish that HR practices help to determine the type, quality, motivation, and deployment of human resources within a firm, which are key dimensions of firm-level human capital heterogeneity (e.g., Chadwick and Dabu 2009; Delery and Shaw 2001; Huselid 1995). Thus, we expect that (in addition to other types of firm-level performance) HR practices influence relative firm-level efficiency, a hypothesis that is heretofore untested in the extant literature.

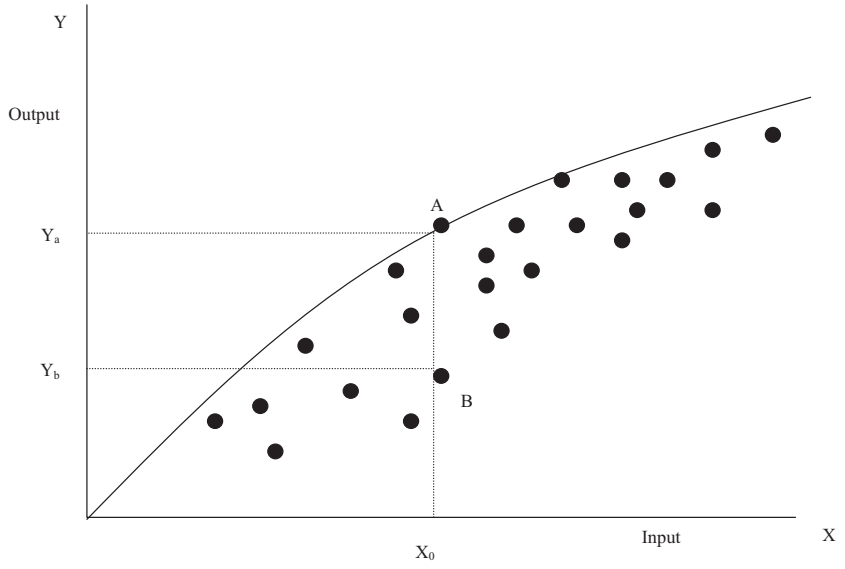
Production Frontiers Analysis

Our analysis utilizes a methodology that is largely unexploited in HRM research, production frontiers analysis. Production frontiers analysis was developed to address circumstances when researchers wish to determine comparative efficiency in a sample of organizations (firms, in this case) where production inputs and outputs may be combined in many different ways (Coelli, Prasada Rao, and Battese 1998). Various manufacturing assembly lines, for example, may employ a number of different production approaches, such as traditional mass manufacturing, lean manufacturing, or mass customization, and may vary in the emphasis placed on disparate outcomes such as scrap rates, product quality, and productivity.

Essentially, production frontiers analysis derives an ''efficiency frontier'' for a sample of cases, akin to a standard macroeconomic production possibilities frontier (Lieberman and Dhawan 2005). The most efficient firms map out the far edge of the frontier, varying in their placement along the frontier according to the different ways that they combine inputs and outputs in their production functions. Less efficient firms have lower relative efficiency scores ranging from a maximum possible efficiency score of one down to zero. Figure 1 illustrates the concept of a production frontier for a sample of firms. Firm A lies on the efficient frontier, whereas Firm B falls below the frontier. Both firms consume the same quantities of inputs. Firm B, however, has lower output and thus lower relative efficiency. The relative efficiency of Firm B is the ratio of B's inputs and outputs compared with that of efficient firms that define the frontier in the sample, such as Firm A. Firm B's efficiency score therefore falls between zero and one. In other words, as Lieberman and Dhawan (2005: 1061) put it, ''efficiency [as determined by a production frontiers analysis] can be thought of as the firm's scaling factor relative to the frontier in the range: $0<TE<1$.'' While production frontiers analysis technically generates efficiency estimates that are relative to the production frontier, because a production frontier analysis is sample specific and is mapped out by the sample's most effi-

FIGURE 1

DEPICTION OF A PRODUCTION FRONTIER



cient firms, the efficiency scores for each firm in the sample are *de facto* estimates of firm efficiency relative to all of the other firms in the sample.

Accordingly, production frontiers analysis allows us to focus on relative firm-level efficiency without reference to a specific HRM production function. In fact, production frontiers analysis allows for equifinality in firm efficiency with respect to HRM, because there are potentially many different configurations of HR practices that would set an establishment on the efficiency frontier.[1] In other words, production frontiers are an analytic approach that can accommodate idiosyncratic HRM production functions across firms and are therefore free of the normative bias favoring commitment-based (or ''high performance'') HRM systems that characterizes much of the extant literature.

Additionally, while OLS assumes that all firms are operating at their highest efficiency, production frontiers analysis is based on the assumption that many firms are operating below the efficiency frontier (Dutta, Narasimhan, and Rajiv 2005). Production frontiers thus allows us to capture variance in firms'

[1] For comparability, the production frontiers analysis in this paper considers firm-level efficiency with respect to the same set of HR practices for all firms in our sample. Production frontiers analysis allows sample firms, however, to vary in the emphasis placed on each HR practice—including no use of a particular HR practice at all—and to vary in the ways that the HR practices' interrelationships are configured.

abilities to effectively implement their sets of HR practices in addition to simply acknowledging the existence of particular HR practices in sample firms.

The Advantages of Stochastic Frontier Production Function Analysis[2]

Researchers may choose from a number of different production frontier methodologies depending on their specific questions and on the data at hand. Perhaps the best known of these techniques is data envelopment analysis (DEA). Data envelopment analysis allows for multiple output variables, which is a strength, but DEA does not give statistical estimates of the effects of individual variables on relative efficiency across the sample because it is a nonparametric analysis. In the past, DEA researchers have often worked around this problem using a two-stage analytic strategy where firms' efficiency scores are first estimated based on a set of basic firm characteristics and then regressed onto a set of explanatory variables (Coelli, Prasada Rao, and Battese 1998). However, this approach is conceptually inconsistent because it combines nonparametric DEA estimates of relative efficiency with parametric regression analysis (Lieberman and Dhawan 2005).

Fortunately, a different parametric form of production frontiers analysis is now available, SFPF. The advantage of SFPF for our purposes is that it simultaneously derives estimates of firm-level relative efficiency for a sample and generates estimates of independent variables' (HR practices') effects on firm-level relative efficiency for the sample generally. In other words, SFPF performs the two-stage analysis that researchers have previously employed with DEA simultaneously within the same parametric model, which is more efficient and theoretically consistent. In contrast to DEA, the SFPF procedure does not allow us to incorporate multiple output variables in the same model, but as our interest in this paper focuses on annual firm sales conditional on a set of controls, this is not a drawback.

In brief, SFPF analysis estimates relative firm efficiency by introducing a two-part error term to a regression model (Greene 2001). The first error term v_i represents the purely stochastic error component affecting the dependent variable, akin to an OLS random error, and it is associated with that portion of the SFPF model that estimates the cross-firm effects of various independent variables on the dependent variable, as in OLS. Conceptually, this error term accounts for random events both external and internal to the firm, as the inde-

[2] We refer the reader to Battese and Coelli (1995); Coelli, Prasada Rao, and Battese (1998); Greene (2001); Dutta, Narasimhan, and Rajiv (2005); and Lieberman and Dhawan (2005) for detailed explanations of stochastic frontier production functions (SFPF) methodology.

pendent variables in this part of the model are production function inputs and firm characteristics that affect the output of firms across the sample generally.

The second error term u_i in an SFPF model captures relative firm-level efficiency (described in production frontiers analysis as ''technical efficiency'') with respect to a set of independent variables (Battese and Coelli 1995). Analytically, efficiency in production frontiers is the ratio of the expected value of the predicted frontier output, conditional on the firm's technical inefficiency (u_i) and a set of firm characteristics, to the expected value of the predicted frontier output conditional on the value of u_i being 0. This efficiency estimation is determined via maximum likelihood. Conceptually, the efficiency estimated here is a firm's relative ability to transform production inputs into an outcome of interest (e.g., annual sales) conditional on a set of firm characteristics specified in the technical efficiency portion of the model. In other words, the variables in this part of the analysis are used to estimate each sample firm's standing relative to the frontier.

The SFPF model in this study can thus be written as

$$y_i = f(x_i; \beta) TE_i \exp(v_i) \tag{1}$$

where y_i denotes the total annual sales of firm i; $\boldsymbol{x_i}$ is a vector of the firm's inputs such as capital inputs, labor inputs, size, etc.; and β is the vector of estimated cross-firm effects of a firm's inputs on its output (i.e., log total sales). Output y_i is determined by the $f(x_i; \beta)$ (which is the production frontier), by TE_i (the technical efficiency of firm i), and by the random error term $exp(v_i)$. Thus, firms where $TE_i = 1$ are at the ''ideal frontier,'' meaning that observed output has reached its maximum obtainable value, given the specification of the model, and have output akin to that which would be estimated under OLS. In contrast, $TE_i < 1$ is a measure of sample firms' shortfalls in efficiency relative to the frontier.

In our analysis, we treat HR practices as characteristics that influence firms' relative efficiency by placing them in the technical efficiency portion of the SFPF model; that is, by treating HR practices as the firm characteristics generating differences in estimated relative efficiency.[3] We parameterized TE_i as the second error term, $u_{i,}$, which is a function of $\boldsymbol{Z_i}$, a vector of firm-specific HR practices such as pay policy, quality meetings, job rotation, training, and selection/recruiting breadth in the following form:

[3] As part of the analysis that we report below, we employed other specifications of the SFPF model that placed some of the control variables in the technical efficiency portion of the model along with the HR practice variables. Our results are largely consistent across these alternative specifications, which suggests that centering our technical efficiency analysis on the HR practice variables does not bias our inferences about their influence on relative firm-level efficiency.

$$u_i = \mathbf{Z}_i\gamma + W_i \tag{2}$$

Because TE_i is required to be ≤1, we can also write this expression as an exponential where $u_i \geq 0$.

$$TE_i = \exp(-u_i) \tag{3}$$

$$TE_i = \exp(-Z_i\gamma - W_i) \tag{4}$$

where γ is a vector of unknown parameters to be estimated in the technical efficiency portion of the SFPF model and W_is are unobservable random variables.

Lopez-Cabrales, Valle, and Herrero (2006) recently employed DEA to evaluate the effects of core employees' attributes on relative firm-level efficiency, the first time that production frontiers methodology has been applied to research on HRM and firm performance. While this study is a good initial step, it also leaves open opportunities for improvement. First, Lopez-Cabrales et al.'s sample is considerably smaller (eighty firms) than the sample that we employ in this paper (n = 1579), limiting generalizability. Second, the Lopez-Cabrales, Valle, and Herrero (2006) study utilizes the theoretically inconsistent DEA two-stage nonparametric/parametric approach to estimating efficiency and evaluating its determinants that we described above. The authors first use DEA to estimate relative efficiency for their set of firms and then regress these efficiency estimates onto a set of variables to infer which firm characteristics drive them. Third (and most importantly), the authors do not directly link HR practices to relative firm-level efficiency.

Data

The data were gathered from a national probability sample of private sector U.S. for-profit establishments (e.g., manufacturing plants or retail stores) with over twenty employees in 1993, a sampling frame representing approximately 85 percent of all establishments in the United States. Corporate headquarters were omitted from the samples. The survey was conducted via telephone interviews by employees of the U.S. Bureau of the Census with at least one Census Bureau contact person at each establishment, each of whom was asked to report on establishment conditions during 1993. In the manufacturing sector, the primary respondents were plant managers. With some restrictions, these data, the National Employers' Survey, are publicly available from the Census Bureau to interested scholars (Cappelli and Neumark 2001).

The fact that a single survey was used to gather each panel can create concerns about measurement error and about spurious correlations between the variables in the analysis (Gerhart et al. 2000). These potential problems are mitigated by the fact that the ongoing informal reporting relationship that existed between the survey respondents and the Census Bureau gave respondents a stronger incentive to provide accurate information than occurs in a single-iteration survey from researchers whom the respondent does not know. Additionally, the surveys were conducted at the establishment level where, as Gerhart et al. observed, ''smaller numbers of employees and presumably greater homogeneity of HR practices might be expected to yield higher reliabilities'' (2000: 829). Moreover, the dependent variable is anchored in factual reports that are readily available to respondents, and the survey was designed so that other respondents could provide those data if the main respondent was unsure about them.

One advantage of using data on the establishment level is that it avoids the questionable assumption that HRM practices are the same across a large and varied firm. Additionally, concerns about the HRM system being widely different across a firm's lines of business are greatly reduced in these data because establishments usually conduct their business in single industries. Indeed, 94.5 percent of the sample's establishments reported that they derived most of their revenues from products within a single industry grouping.

Moreover, because the survey utilized the existing reporting relationships with the Census Bureau, the response rate was 72 percent, which is substantially higher than similar establishment surveys and reduces sample bias concerns. On the basis of its primary line of business, each establishment in the sample was assigned by the Census to one of the twenty-one different industries, organized largely by two-digit SIC code. Probit analysis conducted by Lynch and Black (1995) on the characteristics of non-respondents indicated that there was no significant pattern at the SIC two-digit industry level in the likelihood of participating in the survey.

These advantages, along with the exceptionally large size of the data set for this type of research and the availability of input cost data, make these data well suited to analyzing relative firm-level efficiency with respect to HRM.

Missing Data

Because the analysis employs information from eighty-seven different original survey variables, loss of statistical power from missing data is a potentially serious concern. Although only 7.7 percent the data are missing in the original sample, because these missing data tend to be scattered broadly across cases

and variables, simple casewise deletion of missing data in an analysis utilizing all dependent, HRM, and control variables reduces the usable sample from the original 3167 cases to 732 cases, considerably attenuating statistical power. We are able to mitigate the problem of missing data, however, by utilizing expectation-maximization (EM) imputation of missing values, which employs maximum likelihood to converge iteratively on estimates of the missing values. Analyses using EM estimates of missing data have been demonstrated to be more consistent and efficient than those using regression imputation, mean substitution, casewise deletion, or pairwise deletion because EM employs less-restrictive assumptions. This is especially true as the proportion of missing data and the size of a data set increase (Arbuckle 1994). For ordinal variables, we rounded the EM-imputed values to the nearest integer (Schafer 1997). We do not use imputed values for the dependent variable or for the costs of production inputs variables, resulting in a working sample of 1579 cases.

Variables

The means, standard deviations, and detailed definitions for the dependent, HRM, input costs, and control variables that we use in the analysis are presented in Table 1. We discuss each type of variable in turn in this section.

Dependent Variable. The dependent variable is the natural logarithm of an establishment's total sales for 1993. In estimating relative firm-level efficiency with respect to log of total sales, we account for the costs of labor and capital inputs to establishments' production functions (because such input costs can vary substantially across establishments) as well as for establishment size and other key characteristics. Our use of total annual sales as the dependent variable along with the two costs of production inputs is consistent with production frontiers' input–output approach to estimating efficiency that we described above, while the workforce size variables account for the positive correlation between firm size and total sales. (These input cost variables are described in detail below.) Further, the total annual sales variable is preferable to accounting measures of firm output because it has greater reporting consistency across establishments and also because accounting performance measures are usually unavailable for establishments that are privately held or are part of multi-establishment firms.

HR Practice Variables. We employ ten HR practice variables in our analysis: pay policy, incentive pay, benefits breadth, pay for skill, quality improvement meetings, job rotation, flextime, job sharing, selection/recruiting

TABLE 1

KEY VARIABLE DESCRIPTIONS AND DESCRIPTIVE STATISTICS[a]

Mean	SD	Variables
		Dependent Variable
10.11	1.96	Log of sales: natural log of total establishment sales, receipts, or shipments for 1993.
		HR Practice Variables
0.34	0.38	Pay policy: a weighted average of dummy variables across five broad job classes, each indicating whether the firm pays wages that lead the labor market. Cronbach's $\alpha = 0.82$.
0.54	0.45	Incentive pay: a weighted average of dummy variables across five broad job classes, each indicating whether some form of profit sharing, bonuses, or gain sharing is given to employees. Cronbach's $\alpha = 0.93$
7.59	2.14	Benefits breadth scale: count of the number of different benefits (e.g., dental coverage, pensions, etc., up to eleven benefits) offered by the establishment. Cronbach's $\alpha = 0.72$.
18.99	31.60	Pay for skill: percentage of establishment employees who receive pay for skill or pay for knowledge.
46.81	41.14	Quality meetings: percentage of non-managerial and non-supervisory workers currently involved in quality improvement meetings.
1.32	1.60	[b]Log of job rotation: natural log of the percentage of non-managerial and non-supervisory workers currently involved in job rotation.
0.32	0.46	Flextime: dummy variable indicating that the establishment offers flextime.
0.25	0.43	Job sharing: dummy variable indicating that the establishment allows job sharing between employees.
3.19	0.59	Selection/recruiting breadth: count of the number of different selection criteria used (0–11), weighted by a Likert response about the importance attached to each criterion (1–5 pts.). Cronbach's $\alpha = 0.84$.
9.59	3.24	Training breadth: count of the number of different kinds of training (0-11) offered. Cronbach's $\alpha = 0.81$
		Inputs Costs Variables
12.64	2.52	Log of labor inputs: natural log of the value of labor production inputs for 1993.
13.08	2.89	Log of capital inputs: natural log of the value of capital production inputs for 1993.
		Establishment Characteristics Variables
0.18	0.38	Size 1-49: Dummy variable indicating that the establishment has 1–49 workers.
0.18	0.38	Size 50-99: Dummy variable indicating that the establishment has 50–99 workers.
0.19	0.40	Size 100-249: Dummy variable indicating that the establishment has 100–249 workers. (Omitted category is establishments with 250+ workers.)
0.32	0.46	Unionization: dummy indicating that at least some establishment workers are represented by a labor union.
0.35	0.48	Single establishment: dummy indicating that the establishment is part of a single establishment firm.
8.56	2.25	Log of capital stock: natural log of the total book value of establishment's plant, equipment, and other capital stock for 1993.
0.75	0.43	Founded before 1983: dummy indicating that the establishment was founded before 1983.
1.14	0.46	[b]Log of management levels: natural log of the number of management levels between first-line supervisor and the establishment's top official.
2.17	0.78	[b]Log of percent managers: natural log of the percentage of establishment employees who are managers.
1.07	1.31	[b]Log of percent part-time workers: natural lag of the percentage of establishment employees who are part-time workers.
0.48	0.94	[b]Log of percent temporary/contract workers: natural lag of the percentage of establishment employees who are temporary or contract workers.

TABLE 1 (Cont.)

Mean	SD	Variables
2.24	1.11	[b]Log of realized turnover: natural log of the percentage of establishment workers who have been with the firm for <1 year.
13.11	35.66	Percent employment increase: percentage increase in the establishment's number of employees over the past 3 years.

NOTES: [a]n = 1579.
[b]Natural logs for these variables taken after adding a constant of one (see text).

breadth, and training breadth. As a group, these ten HRM variables reflect the kinds of practices that have been utilized in the previous research on HRM and firm performance, which has emphasized areas such as compensation (pay policy, incentive pay, benefits, pay for skill), participatory management (quality improvement meetings), flexible work organization (job rotation), employment flexibility (flextime, job sharing), selection (selection/recruiting breadth), and training (training breadth). Detailed descriptions of these HR practice variables appear in Table 1. Job rotation is expressed as a natural logarithm to reduce non-normality in its distribution (before taking this logarithm, we added a constant of one to avoid losing cases that have zero values for job rotation). Some control variables were also logged in this way, as indentified in Table 1. The selection/recruiting breadth and training breadth HR practice variables capture establishments' degree of practice implementation in terms of the number of different ways that firms carry out selection/recruiting and training, respectively. The selection/recruiting breadth variable also weights each type of selection/recruiting by the importance ascribed to it by establishments in making their selection/recruiting choices and is the mean across all selection/recruiting practices. The HR practice variables vary in their correlations with log of sales and in their generally low inter-correlations (available upon request) supporting our choice to utilize the HR practices as a set of separate independent variables in our analysis.

Inputs Costs Variables. The labor and capital inputs variables are determined from two different survey questions. The first question asks about establishments' annual total production inputs costs: ''During calendar year 1993, what was the cost of goods and services used in the production of your 1993 sales (for example energy costs, raw materials, and intermediate goods)?'' A second survey question enables us to partition this total production inputs variable into separate capital inputs costs and labor inputs costs variables: ''What percentage of this establishment's total cost of production is accounted for by labor costs?'' Thus, the capital inputs variable is capital in the broad sense of traditional economics, that is, all non-labor production inputs, not simply capital goods inputs. Note that there is a separate control variable for

the value of a firm's capital stock, which is distinct from the annual capital (or non-labor) inputs to an establishment's production process described here. Capital inputs and labor inputs are positively correlated (0.62, $p < 0.05$). These variables are measured in absolute amounts rather than as percentages of total production inputs, which would lead to a negative correlation.

Control Variables. The control variables capture key establishment characteristics that may plausibly be correlated with both establishment performance and the HR practice variables. Many of these controls have been employed in the previous research on firm-level labor productivity. These include labor inputs (e.g., Dunlop and Weil 1996), capital inputs, the value of establishments' capital stocks (e.g., Huselid, Jackson, and Schuler 1997; Koch and McGrath 1996), the number of management levels in the establishment, the percentage of employees who are managers (e.g., Delaney and Huselid 1996), the percentage of employees who are part-time workers, the percentage of employees who are temporary or contract workers, the percentage of the workforce who are new to the establishment within the last year (i.e., realized turnover), and the percentage increase in the establishment's workforce over the previous 3 years. (While turnover is usually a rate, the realized turnover variable is a reasonable measure when the analysis also controls for overall growth in establishment workforces, which could also lead to higher proportions of newer employees in an establishment's workforce.)

The controls also include dummy variables indicating the approximate size of the establishment in employees (cf. Koch and McGrath 1996; Wright et al. 1999; Youndt et al. 1996), unionization (e.g., Arthur 1994; Koch and McGrath 1996), whether the establishment was founded before 1983, whether the establishment is in a single establishment firm (Chadwick 2007), and industry dummies at the two-digit SIC code level (e.g., Huselid 1995; Koch and McGrath 1996).

Results

The first model in Table 2 reports an OLS regression utilizing the full set of control variables except for the two inputs cost variables. (All regressions are weighted by a term that accounts for deviations in the Census' sample frame from a completely random sample of U.S. establishments.) These results generally run in reasonable directions and are largely stable across the regression models reported in Table 2. For example, the size dummies indicate that greater establishment size is associated with higher sales, as is capital stock and increases in the size of the establishment workforce. The inclusion of the

TABLE 2

OLS Regression and SFPF Results for the HRM Practice Variables[a]

	Model 1	Model 2	Model 3	Model 4
	OLS controls model	OLS controls + HRM model	OLS main model	SFPF main model[b]
General effects variables				
Constant	5.950 (0.282)***	5.120 (0.332)***	4.134 (0.395)***	5.240 (0.349)***
Log of labor inputs			0.125 (0.015)***	0.136 (0.016)***
Log of capital inputs			0.091 (0.013)***	0.117 (0.014)***
Industry controls	Yes	Yes	Yes	Yes
Size 1	−0.727 (0.122)***	−0.801 (0.122)***	−0.689 (0.136)***	−1.230 (0.118)***
Size 2	−0.557 (0.121)***	−0.552 (0.119)***	−0.352 (0.128)**	−1.060 (0.097)***
Size 3	−0.175 (0.126)	−0.219 (0.123)†	−0.035 (0.134)	−0.674 (0.087)***
Unionization	0.253 (0.097) **	0.240 (0.100)*	0.229 (0.102)*	0.083 (0.068)
Single establishment	−0.198 (0.064)**	−0.153 (0.066)*	−0.098 (0.070)	−0.207 (0.064)**
Log of capital stock	0.493 (0.018)***	0.442 (0.019)***	0.288 (0.022)***	0.241 (0.019)***
Founded before 1983	−0.251 (0.062)	−0.172 (0.062)**	−0.035 (0.067)	−0.058 (0.068)
Log of management levels	0.169** (0.063)	0.190 (0.064)**	0.024 (0.070)	0.180* (0.071)
Log of percent managers	0.055 (0.036)	0.025 (0.037)	−0.049 (0.041)	0.090* (0.037)
Log of percent part-time workers	−0.128 (0.021)***	−0.112 (0.022)***	−0.163 (0.024)***	−0.044† (0.026)
Log of percent temporary/ contract workers	0.081* (0.035)	0.065 (0.034)†	0.117 (0.037)**	0.079 (0.031)*
Log of realized turnover	−0.018 (0.028)***	−0.081 (0.028)**	−0.014 (0.029)	−0.056† (0.029)
Percent employment increase	0.003 (0.001)***	0.003 (0.001)***	0.002 (0.001)**	0.001 (0.001)
Error term				0.047 (0.052)
Technical efficiency variables (HR practices)				
Pay policy		0.144 (0.081)†	0.253 (0.087)**	−0.493 (0.362)
Incentive pay		0.413 (0.069)***	0.258 (0.074)**	−0.186 (0.311)
Benefits breadth		0.046 (0.017)**	−0.003 (0.019)	−0.685 (0.298)*
Pay for skill		−0.002 (0.001)†	−0.003 (0.001)**	0.033 (0.053)
Quality meetings		0.001 (0.001)	−0.002 (0.001)*	0.091 (0.064)
Log of job rotation		−0.035 (0.019)†	−0.087 (0.021)***	0.010 (0.059)†
Flextime		−0.387 (0.067)***	−0.069 (0.074)	0.583 (0.208)**
Job sharing		0.307 (0.071)***	0.224 (0.079)**	−0.439 (0.266)†

TABLE 2 (Cont.)

	Model 1	Model 2	Model 3	Model 4
	OLS controls model	OLS controls + HRM model	OLS main model	SFPF main model[b]
Selection/recruiting breadth		0.196 (0.052)***	0.199 (0.056)***	2.493 (0.757)**
Training breadth		−0.007 (0.010)	0.016 (0.011)	−0.267 (0.216)
Inefficiency constant				−2.636 (1.102)*
n	1579	1579	1579	1579
F-statistic	83.271***	62.448***	48.259***	
Adjusted R^2	0.433	0.461	0.489	
Change in Adjusted R^2	–	0.028	0.056	
Log Likelihood				−2408.73
Chi squared (degrees of freedom)				2403.46 (47 df)***

NOTES: † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a]Standard errors are in parentheses.

[b]SFPF coefficients for HR practice variables should generally be interpreted opposite of their OLS counterparts (see Results section text).

size dummies conditions the results on the size of establishments' workforces, making the OLS regressions for log of sales not simply estimations of establishment size. The adjusted *R*-squared indicates that this model explains a reasonable amount of the variance in establishment log of sales.

The second model in Table 2 adds the HR practice variables to the first regression. Here, pay policy, incentive pay, benefits breadth, job sharing, and selection/recruiting breadth are associated with higher sales, conditional on establishment size, capital and labor inputs, and so forth. On the other hand, pay for skill, job rotation, and flextime are associated with lower sales with the same controls. In all, eight of the ten HR practice variables have significant coefficients in this regression. The mixed nature of the HR practices' results here again supports our decision to model them as a set of separate variables. This second model is akin to the usual approach to estimating the effects of HR practices on firm-level productivity in the literature, although we depart somewhat from convention in utilizing the HR practices separately rather than as part of a factor or index, because the intercorrelations between HR practice variables do not support such an approach.

Following the prescriptions of those who advocate accounting for labor costs in estimating the effects of HR practices on firm-level productivity, the third regression in Table 2 adds the two inputs costs variables, labor inputs and capital inputs, to the previous OLS model. These two variables are indeed important, generating significant positive coefficients and boosting the model's adjusted R-squared from 0.46 to 0.49. A few of the control variables' coefficients change when we include the inputs costs variables, notably the coefficients for the single establishment dummy and for log of management levels. More importantly, some of the HR practice variables' results change in this model, as well. The coefficients for benefits breadth and flextime become non-significant in this model, while the coefficient for quality meetings becomes significant and pay policy and job rotation have enhanced significance. Additionally, a number of the significant HR practices that carry over from Model 2 have smaller coefficients in Model 3. Indeed, the change in adjusted R-squared that comes from adding the HR practice variables to the ''controls only'' model drops from 0.028 (the difference between Model 1 and Model 2 in Table 2) to 0.017 once the costs variables are included in both models (the latter figure is based on comparison between Model 3 and a regression that includes both the full controls and the input costs variables; results omitted for parsimony). In all, seven of the ten HR practice variables have significant coefficients in Model 3. These results demonstrate that accounting for costs sharpens our understanding of the relationships between the HR practice variables and log of sales, as expected, because omitting labor and capital input costs tends to overstate the strength of these relationships. However, accounting

for such costs is an incomplete approach, as it still does not accommodate HRM production functions that are idiosyncratic across establishments.

SFPF results. To address the issue of idiosyncratic HRM production functions, we employ stochastic frontier production function methodology. The last model in Table 2 reports the results for the SFPF estimation for the same set of variables that appear in Model 3. Although the values generated by the SFPF procedure represent relative firm-level efficiency with respect to HRM, strictly speaking, the second part of the SFPF model is an estimate of independent variables' effects on relative *inefficiency,* and coefficients generated by this part of the SFPF model are interpreted accordingly. These interpretations can be somewhat non-intuitive: Whereas in the OLS models, a positive coefficient suggests that an independent variable is generally a ''good thing'' for establishments, a positive coefficient in the technical inefficiency of the SFPF model associates inefficiency increases with an independent variable, which is generally bad for establishments. Similarly, a negative coefficient indicates that an HR practice is associated with reduced inefficiency (i.e., greater efficiency), which is generally good for establishments.

The parameter estimates for the general effects part of the first SFPF model in Table 2 (Model 4), as expected, parallel the regression results for these variables, with very few differences in signs or significance between the estimates in Model 3 and Model 4. However, the SFPF model generates different results for the HR practice variables. Five of the ten HR practices are significantly related to the relative efficiency of sample establishments, as hypothesized. As we detail in the Discussion section, these general relationships with efficiency across establishments do not preclude more idiosyncratic combinations of the HR practices being associated with greater or lesser relative efficiency for specific sample establishments. In this model, benefits breadth and job sharing are associated with greater relative establishment efficiency, while job rotation, flextime, and selection/recruiting breadth are related to lower relative establishment efficiency. Of these five significant HR practices, benefits breadth and flextime do not have significant relationships with log of sales in the equivalent OLS model, Model 3.

A key output of Model 4 is estimated establishment efficiency concerning the HR practice variables. The efficiency scores generated by the first SFPF model in Table 2 suggest that many establishments' efficiency scores with respect to HRM cluster pretty closely. Specifically, the mean efficiency score from Model 4 and the median and standard deviation of these scores are 0.63, 0.63, and 0.10, respectively, indicating fairly tight clustering and little skew in the efficiency scores' distribution. In fact, only fifty-four establishments lie further than two standard deviations below the mean efficiency score.

Discussion and Supplemental Analysis

Overall, the results from our analysis support the argument that estimating HR practices' relationships with relative firm-level efficiency is a useful way to evaluate firm-level labor productivity. Moreover, estimating relative firm-level efficiency with respect to HRM provides different information than the analytic approach commonly employed in the extant literature. The SFPF model demonstrates that HR practices significantly influence differences in relative firm-level efficiency in our sample. Some HR practices are associated with greater firm-level relative efficiency, other HR practices have the opposite relationship, and a number of the HR practices do not have significant relationships with relative firm-level efficiency. It is important to note in this regard that a great many differences in relative firm-level efficiency with respect to HRM are firm specific and thus not discernable through the coefficients generated in the SFPF analysis, which reflect the general relationships between HR practices and relative efficiency across the sample's establishments.

To illustrate the variation in establishment-specific HRM production functions that occur within the sample, Table 3 reports the values for the ten HR practice variables for selected individual establishments from the opposite ends of the estimated efficiency variable's distribution. The first five columns in Table 3 report HRM practice data for the five establishments with the highest estimated relative efficiency scores (based on the first SFPF model in Table 2). The second five columns in Table 3 report corresponding data for the five establishments with the lowest estimated relative efficiency scores (based on the same model). As these data suggest, establishments in the sample utilize HRM in very different ways, even when these establishments are the cases defining the efficiency frontier. Note, for example, how establishments' use of the five HRM practices that have significant coefficients in the SFPF model in Table 2 (benefits breadth, job rotation, flextime, job sharing, and selection/recruiting breadth) vary across the establishments in Table 3. Perhaps even more revealing is the variation among the high-efficiency establishments. For instance, High-Efficiency Establishment five engages in eight of the ten HR practices (some of these practices, such as pay for skill, rather heavily), thus generally matching popular notions of ''high performance'' HRM systems. On the other hand, High-Efficiency Establishment three only engages in four of the ten HR practices that we studied. Three of these practices involve compensation (pay policy, incentive pay, and broad benefits), and the other HR practice indicates a very low level of its workforce involved in quality meetings. Yet, despite these different HRM configurations, both of these establishments have very high levels of estimated relative efficiency with respect to HRM. Accommodating this

TABLE 3

HRM Practice Variable Values for Selected Establishments

Establishments										
HRM variables	High Efficiency 1	High Efficiency 2	High Efficiency 3	High Efficiency 4	High Efficiency 5	Low Efficiency 1	Low Efficiency 2	Low Efficiency 3	Low Efficiency 4	Low Efficiency 5
Pay policy	1.00	0.00	1.00	0.00	1.00	0.00	0.84	0.15	0.43	0.00
Incentive pay	0.60	0.00	1.00	0.00	1.00	0.00	0.84	0.15	0.43	0.00
Benefits breadth	10.00	0.00	1.43	0.88	0.00	0.00	1.00	1.00	1.00	0.25
Pay for skill	0.00	4.00	9.00	5.00	5.00	7.00	8.00	10.00	9.00	9.00
Quality meetings	3.00	0.00	0.00	0.00	100.00	15.00	0.00	0.00	0.00	10.00
Job rotation[a]	3.00	10.00	1.00	100.00	0.00	4.00	100.00	100.00	100.00	50.00
Flextime	0.00	15.00	0.00	10.00	33.00	0.00	10.00	20.00	50.00	2.00
Job sharing	0.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00
Selection/recruiting breadth	2.82	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00
Training breadth	11.00	4.36	3.27	3.82	3.27	3.55	3.73	4.18	4.27	2.82

Note: [a] To enhance interpretability, values for this HRM practice variable are not reported for its logged version.

variation across firms is a major strength of the production frontiers approach, as it allows HRM researchers to acknowledge HRM equifinality arguments analytically.

A Comparison of Relative Firm-level Efficiency with Respect to HRM to the OLS Estimate of HRM's Impact. We have compared two approaches for evaluating HR practices' relationships with firm-level labor productivity in this paper. The differences between these two approaches deserve a little further scrutiny. To do this, we constructed a summary of the OLS estimates of the ten HR practices' relationships with log of sales. We first multiplied each HR practice variable by its coefficient from Model 3 in Table 2 and then summed the resultant products to derive a measure that we label ''OLS returns to HRM.'' OLS returns to HRM are positively correlated with the efficiency scores generated by the SFPF model in Table 2 (0.17, $p < 0.001$), but the correlation is low enough to suggest that the two methodologies do indeed capture different forms of firm-level labor productivity.

Next, we built Table 4 to get a rough idea of these constructs' comparative relationships with establishment performance. Each axis of Table 4 is based on one of the two constructs, relative firm-level efficiency with respect to HRM and OLS returns to HRM, split at their medians. Our outcome in this table is the residuals from an OLS regression employing all of the control variables that appear in Model 3, Table 2, including the labor and capital input costs variables (regression not shown). As the residuals from this model are the variance in log of sales that is not attributable to the controls, they account for the effects of factors other than the HR practices on establishments' total sales revenue, including establishment size, unionization, capital intensity, etc.

The top numbers in each of the four cells in Table 4 report mean residual log of sales for the establishments that fall within that cell, while the bottom number in each cell reports the number of establishments in that cell. As

TABLE 4

OLS Returns to HRM, Relative Firm-Level Efficiency with Respect to HRM, and Residual Establishment Performance

	Relative firm-level efficiency with respect to HRM	
	Low	High
OLS Returns to HRM		
Low	−0.31	0.74
	$n = 456$	$n = 334$
High	−0.39	0.88
	$n = 333$	$n = 456$

Table 4 illustrates, the differences in mean residual log of sales based on the median split in OLS returns to HRM are small, but the differences in mean residual log of sales based on the median split in relative firm-level efficiency with respect to HRM are large and change signs. Establishments high in efficiency have positive residual log of sales, while establishments low in efficiency have negative residual log of sales. This exploratory table, while far from definitive, therefore implies that relative firm-level efficiency with respect to HRM is more important for establishment performance than HR practices' estimated effects on revenue (i.e., OLS returns to HRM).

Limitations. As in any study, there are limitations to our efforts. As this paper is the first to examine the relationships between specific HR practices and relative firm-level efficiency, we did not hypothesize about which individual HR practices would have significant relationships to relative firm-level efficiency. Such hypothesizing awaits further empirical results that flesh out the causal mechanisms driving individual HR practices' relationships with relative firm-level efficiency. Moreover, we suspect that individual HR practices affect relative firm-level efficiency differently in different samples. Future research in other data sets could examine how contextual factors may affect the relationships that we find here. Additionally, future research could explore the role of mediators between HR practices and relative firm-level efficiency, such as human capital as suggested in the Lopez-Cabrales, Valle, and Herrero (2006) study that we cited earlier. Furthermore, while it would be preferable for comparability to have a continuous measure of workforce size to estimate sales per employee, the OLS results' consistency with the published findings in the HRM and firm performance literature suggest that the workforce size dummies make a reasonable accounting for size effects.

As with all cross-sectional studies, endogeneity is a potential concern in this research. The type of endogeneity that has most often been raised as a potential weakness in research on HR practices and organizational performance is simultaneity. Because many commitment-based HR practices incur significant administrative expenses, it may be the case that higher performing firms are better able to afford such practices. Positive cross-sectional relationships between performance and HR practices may therefore be a consequence rather than a cause of higher organizational performance. It is possible that this is the case in these data, but there are two reasons to believe that endogeneity is a lesser threat to this paper's conclusions than it is in typical HRM/organizational performance research.

First, the conceptual argument about simultaneity involves, as we noted, positive relationships between organizational performance and HR practices. In this paper's SFPF analysis, this reasoning would apply when HR practices are

significantly associated with higher establishment relative efficiency. This is indeed true of two of our HR practices, benefits breadth and job sharing. However, three other HR practices, job rotation, flextime, and selection/recruiting breadth, are significantly related to *lower* relative establishment efficiency. In other words, endogeneity bias because of simultaneity should be confined to benefits breadth and job sharing in our analysis, because it is difficult to imagine how establishments that are inefficient would be prompted by their inefficiency to employ job rotation, flextime, and greater selection/recruiting breadth. Moreover, a comparison of the control variables in the analysis shows few systematic differences between establishments that are high and low on job sharing, although this same difference is significant on all of the key establishment characteristics variables for the benefits breadth variable. Thus, while simultaneity cannot be definitively ruled out, particularly for benefits breadth, it appears to be an inadequate explanation for a good number of the significant relationships of interest in our SFPF model.

Second, the SFPF technique itself may offer protection against biased inference because of endogeneity. Researchers in production frontiers methodology have traditionally assumed that endogeneity is not a threat to inference in their analyses because production frontiers is ''a boundary technique that merely models feasible relationships between inputs and outputs'' in a sample (Orme and Smith 1996: 75). With respect to DEA, however, Orme and Smith (1996) demonstrated with simulation data that endogeneity could bias inference in production frontiers models that use small samples, but that endogeneity bias is mitigated in DEA that uses large samples. Bifulco and Bretschneider (2001) challenge this proposition, and their results are, in turn, disputed by Ruggiero (2003). The latter author claims that DEA handles endogeneity very well in samples that are larger than 500 cases, a criterion that is clearly exceeded by this paper's data set. Moreover, the logic employed by these scholars extends from DEA to SFPF.

This debate has not yet been completely resolved subsequent to the above publications, but the current conclusions are favorable for our analysis, as they predict an attenuation of endogeneity bias in larger production frontiers samples like the one that we employ in this paper. Nevertheless, we hope that future research that uses production frontiers to examine HRM and organizational relative efficiency will have more concrete guidelines concerning endogeneity to follow. In general, it is clear that research concerning HRM and organizational performance must account for the possibility of endogeneity bias. Indeed, without the advantages of production frontiers modeling, it is possible that traditional OLS models of profitability and HRM could face endogeneity issues even in this same data set.

Conclusion

Clearly, our understanding of how HRM influences relative firm-level efficiency is only a beginning. However, our analysis demonstrates the usefulness of the relative firm-level efficiency concept in HRM research. Production frontiers adds valuable new perspectives to HRM's impact on firm-level labor productivity that complement what can be learned from the usual approach in the literature. To scholars outside of HRM, this study demonstrates that people management practices are an important determinant of variance in essential competitiveness—that is, relative efficiency—across firms. Multiple analytic approaches are becoming increasingly important in research linking HRM with firm performance as researchers work to uncover the causal mechanisms driving both efficiency and competitive advantage through people. It is more complete approaches like these that will help us to better specify how and why people management matters to firms.

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