The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines

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We investigate the productivity effects of innovative employment practices using data from a sample of 36 homogeneous steel production lines owned by 17 companies. The productivity regressions demonstrate that lines using a set of innovative work practices, which include incentive pay, teams, flexible job assignments, employment security, and training, achieve substantially higher levels of productivity than do lines with the more traditional approach, which includes narrow job definitions, strict work rules, and hourly pay with close supervision. Our results are consistent with recent theoretical models which stress the importance of complementarities among work practices. (*JEL* J24, J5, L20, M11)

This study presents new empirical evidence on the productivity effects of alternative employment practices using data that we have assembled on steel finishing processes. The unique data set makes this study's estimates of productivity differentials due to employment practices particularly convincing for several reasons. First, the data set is restricted to observations on one very specific type of manufacturing production process. This narrow focus eliminates many sources of heterogeneity that confound productivity comparisons in more aggregate data and in more heterogeneous samples. Second, we develop a detailed model of this particular production process based on personal visits to each work site. We estimate the productivity model using precise measures of productivity, capital equipment, employment practices, and other line-specific determinants of productivity that we collected from each work site. Third, we obtain longitudinal data on each production line to estimate fixed-effects models that investigate changes in productivity within production lines due to changes in their employment practices. The primary limitation of the study is, of course, that it reflects work practices and performance outcomes in only one industry.

We find consistent support for the conclusion that groups or clusters of complementary human resource management (HRM) practices have large effects on productivity, while changes in individual work practices have little or no effect on productivity. In Section I we describe the unique sample and data assembled for this study. Section II identifies studies in the incentive contract literature which stress the importance of complementarities among employment practices, while Section III develops measures of the production lines' HRM practices. In Sections IV–VI we present alternative econometric specifications of the productivity model and the empirical estimates. Section VII offers a conclusion.

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I. Sample and Data

A. *Sample Design*

Heterogeneity in production processes and outputs often limits the persuasiveness of empirical studies that make firm-level or plant-level productivity comparisons. Therefore, in designing our model of worker productivity, we sought to minimize heterogeneity by collecting a unique data set on a sample of steelmaking operations. Observations in the sample are not of steel companies, divisions of steel companies, or even steel mills. Rather, the sample consists of observations on one very specific type of steel finishing process.

Of the approximately 60 finishing lines of this type in the United States, we personally visited 45 lines owned by 21 companies at locations ranging from New York to Alabama to California. We conducted field interviews for one to three days at each site, collecting information on HRM practices, the performance of the finishing lines, the capital equipment used in the production processes, other inputs into the production process, and wage data. Four of the 45 lines could not provide performance data because they had been operating for only a few months. Of the remaining 41 lines, 36 lines provided comparable monthly productivity data.

This study's econometric analysis uses a panel data set of up to 2,190 monthly observations on the productivity of these 36 steel finishing lines owned by 17 different steel companies. The sample includes multiple lines for major steel producers as well as lines for smaller companies that operate only one or two lines. The sample contains unionized lines as well as nonunion lines. According to company and industry sources, the sample includes high and low performers and a wide range of HRM environments.

B. *The Production Process and the Dependent Productivity Variable*

To understand how to model the production process in these finishing lines and how to measure the lines' performance, we toured each line with an experienced engineer, area operations manager, or superintendent. The basic production process is very similar in all lines. Steel input on each line is a roll (or coil) of flat-rolled steel weighing about 12 tons. The coil is loaded at the beginning of the line where the steel strip is welded to the end of the previous coil on the line. The coil then is unrolled so that a long, continuous sheet of steel threads its way through the machinery that treats the steel. After the finishing treatment, the steel strip is then re-coiled and cut at the exit end of the process. The line can operate continuously around the clock as coils are welded to one another.

The productivity model for this production process is best understood within the context of an "engineering production function." The tonnage that comes off the line per month (Q) is a function of the tonnage loaded onto the line—and therefore is a function of the width (w) and thickness or gauge (g) of the steel strip—times the speed of the line (s), and the hours it is running (h). If h^s represents the maximum hours the line is scheduled to run, then the potential steel output on line i in month t is arithmetically determined by the four key technical parameters (w, g, s, and h^s), and this can be expressed:

$$(1) \quad \text{Potential } Q_{it} = \omega(w_{it} \cdot g_{it} \cdot s_{it} \cdot h^s_{it}),$$

where the quantity in parentheses in equation (1) is the volume of steel through line i in month t, and ω is an estimate of the density of steel.

Since the production parameters in equation (1) are determined by the technical specifications of the line's equipment and the specifications of the input coil's width and gauge, a line's production in any month depends only on the number of hours the line actually runs:

$$(2) \quad \text{Actual } Q_{it} = [\omega(w_{it} \cdot g_{it} \cdot s_{it} \cdot h^s_{it})] \times (1 - d_{it}),$$

where d_{it} is delays—the fraction of total scheduled hours that are lost because of unscheduled line stops. Once the technological parameters and product mix are specified, *production depends solely on delays. Productivity improves by increasing uptime,* $(1 - d_{it})$.

Production-line uptime is our primary measure of productivity, because uptime directly determines steel output and because uptime figures are especially comparable across companies. Uptime, $U_{it} = 1 - d_{it}$, is the percent of scheduled operating time that the line actually runs. In the sample of 2,190 ''line-month'' observations used in the empirical analysis, uptime has a mean value of 0.919, a standard deviation of 0.044, and a range of 0.398 to 0.996. In addition to this output measure, we will provide results for the quality of output, as measured by the percent of tons produced that meet specific quality standards for the industry. We focus primarily, however, on productivity.

C. *Control Variables in the Productivity Equation*

This study's focus on one specific production process eliminates many sources of heterogeneity in productivity, but these production lines are not identical. To provide a thorough set of controls for other sources of productivity variation, we personally inspected each production line in the sample and discussed with engineering experts from the lines any technical features that affect uptime. Based on these discussions, we were able to identify and collect a comprehensive set of data on technological features of the lines that affect their productivity.

The uptime productivity equations include up to 25 controls for detailed features of the line that affect uptime. These are controls for capital vintage (the year the line was built and its square); ''learning curve'' effects (time since start-up of the line and its square, a dummy for the first year of operations, and a monthly time counter for the start-up period); technical line specifications (line width, line speed, and their squares); specific line machinery that reduces or increases the likelihood of unscheduled downtime (a dummy for the degree of computerization on the line and nine dummies for specific design features of equipment); periods of unusually high downtime (variables for quarters when new equipment is added to the line); the quality of steel input (a ranking of steel quality from potential U.S. suppliers); and the extent of scheduled downtime for maintenance activities (the number of annual eight-hour maintenance shifts). According to our interviews and site inspections, unscheduled downtime should be higher in older lines, faster and wider lines, start-up periods, lines with fewer computerized controls, periods when new equipment is installed, lines that perform less preventive maintenance, and lines with lower quality steel input.

D. *Data on HRM Policies*

We gathered human resource management data by conducting standardized interviews with HR managers, labor relations managers, operations managers of the finishing lines, superintendents, line workers, and union representatives in organized lines. We collected supporting information from personnel files, personnel manuals, collective bargaining agreements, and other primary source documents. We used this information from the interviews and supporting documents to answer survey-type questions about the HRM practices and then to construct a detailed set of HRM dummy variables.

Table 1 provides the definitions of a subset of representative HRM variables and their mean values for the panel data set. These variables measure work practices in all major areas of personnel management, including compensation, recruiting and selection, team-based work organization, employment security, flexible job assignment, skills training, and communication procedures. We also include two traditional labor relations indicators: the union status of the line and a grievance rate variable.

II. Complementarities Among Work Practices

Several empirical studies have examined the effects on a firm's productivity of individual work practices such as those listed in Table 1, including profit sharing (Douglas L. Kruse, 1993), training (Ann Bartel, 1995), or information sharing (Morris Kleiner and Marvin Bouillon, 1988). However, recent incentive contract theories argue that complementarities

TABLE 1—DEFINITIONS OF HRM VARIABLES

HRM variable name	Mean	Dummy variable description
1. *Incentive pay*		
a. Profit sharing	0.700	Is there a company profit-sharing plan covering the line workers?
b. Line incentives	0.186	Are operators covered by a "nontraditional" incentive pay plan which applies across shifts of workers and which is sensitive to quality as well as quantity aspects of output?
2. *Recruiting and selection*		
a. High screening	0.085	Was an extensive selection procedure used to hire new workers, including tests for personality traits needed for cooperative team environments and efforts to set clear expectations about required work behaviors of the new workers?
3. *Teamwork*		
a. High participation	0.237	Are a majority of operators involved in formal or informal work teams or other related problem-solving activities?
b. Multiple teams	0.130	Do operators participate in more than one problem-solving team?
c. Formal team practice	0.335	Are operators organized into formal work teams either on the line or for the purposes of problem-solving activities according to an established policy with at least some operators involved in team activities?
4. *Employment security*		
a. Employment security	0.288	Has the company committed to a goal of long-term employment security and offered employees a pledge of employment security?
5. *Flexible job assignment*		
a. Job rotation	0.079	Do operators rotate across jobs or tasks on the line?
6. *Skills training*		
a. High train	0.134	Have all operators on the line received off-the-job training?
b. Low train	0.208	Have at least some operators received off-the-job training?
7. *Communication*		
a. Information sharing	0.566	Are operators and union representatives, if any, provided with financial information on a regular basis?
b. Meet workers	0.508	Do line managers meet off-line with operators to discuss issues of concern, including issues related to performance and quality?
c. Meet union	0.224	Do union representatives and managers meet often to discuss concerns and cooperate in finding solutions to issues?
8. *Labor relations*		
a. Union	0.917	Is the line a unionized operation?
b. Low grievance	0.499	Is the grievance filing rate less than 12 per year?

Notes: Means reported in column 2 refer to the means for the main sample of N = 2,190 line-months used in the productivity models reported in Tables 4 and 5. For the meet union and low grievance variables, we assign nonunion lines a value of 1 for these two dummy variables because of regular meetings with worker representatives and low levels of complaints in their formal or informal complaint or grievance procedures. The means of these two variables among the sample of union observations are 0.153 and 0.453, respectively.

often exist among a firm's employment practices. For example, one employment practice, such as the use of problem-solving teams, may be more effective in stimulating worker productivity when it is adopted in concert with other work practices that give workers the incentive and the ability to perform well in teams—practices such as incentive pay, training, the flexible assignment of workers, or employment security. These theories argue that is important to analyze a firm's work policies "not in isolation, but as part of a coherent incentive system" (Bengt Holmstrom and Paul Milgrom, 1994 p. 990; see also Milgrom and John Roberts, 1990, 1995; Eugene Kandel and Edward Lazear, 1992; George Baker et al., 1994).

According to these theories, interaction effects among HRM policies are important determinants of productivity. Firms realize the largest gains in productivity by adopting clusters of complementary practices, and benefit little from making "marginal" changes in any one HRM practice. These theories also identify complementarities among specific practices which span seven different HRM policy areas: incentive compensation plans, extensive recruiting and selection, work teams, employment security, flexible job assignment, skills training, and labor-management communication.[1] Taken as a whole, these theories also predict that adopting this entire complement of practices across all seven HRM policy areas will produce the highest levels of productivity.[2]

If firms adopt work practices in a complementary fashion, then empirical tests should consider the impacts of groups of practices rather than simply the effects of individual practices. The primary hypothesis investigated in the empirical work is: *do groups of innovative HRM practices increase productivity?* The productivity effects of groups of innovative work practices also will be compared to the effects of differences in individual work practices.

III. HRM Systems

The argument that complementarities exist among HRM practices is consistent with the evidence that HRM policy variables are highly correlated with each other in our steel sample. Out of 78 possible bivariate correlations among the 13 HRM variables listed in Table 1, 71 are positive and 48 are positive and significant.[3]

Patterns in these correlations are consistent with the predictions of several authors. For example, Kandel and Lazear (1992) show how careful employee recruiting and team meetings can make group incentive pay more effective. In our data, line-specific incentive pay plans (line incentives in line 1b of Table 1) are

[1] As examples, Kandel and Lazear (1992) show that teamwork and careful employee selection will make group-based incentive pay more effective by reducing free-rider problems. Baker et al. (1994) show that incentive pay plans based on objective performance measures can increase the effectiveness of policies such as work teams, which require subjective evaluations of employees. Holmstrom and Milgrom (1994) model the complementarities that arise when workers perform multiple tasks and no one practice induces optimal effort on all tasks. Milgrom and Roberts (1995) argue that productivity-improvement teams are more effective when a firm adopts a set of complementary practices including employment security, flexible job assignments, skills training, and communication procedures. For further discussion of the predictions of these theories, see Ichniowski et al. (1995 pp. 2–7).

[2] The overlap among the policies considered in the theories discussed in footnote 1 implies that the most productive HRM system will have innovative work practices in all seven HRM areas. For example, Baker et al. (1994) consider complementarities between objective incentive pay and subjective performance appraisals or problem-solving teams. But Kandel and Lazear (1992) argue that careful screening, indoctrination, and teamwork make objective incentives more effective, so these policies should be complements with policies like work teams, which require subjective appraisals of employees. Milgrom and Roberts (1995) also consider work teams, but indicate that this policy will be more effective in combination with job security, job flexibility, training, and communication.

[3] To construct the sample for calculating these correlations, we allow one observation for each distinct combination of HRM policies experienced by a line. The 36 production lines experienced a total of 54 different combinations of the HRM practices listed in Table 1, and these 54 observations comprise the sample for calculating correlations among the HRM practices.

positively correlated with extensive recruiting (high screening, line 2a), with team-based work structures (formal team practice, line 3c and multiple teams, line 3b), and with labor-management meetings (meet workers, line 7b and meet union, line 7c). Baker et al. (1994) argue that incentive pay based on objective measures will be complementary to incentive pay based on subjective evaluations of employees. The data here show that the line incentives variable also is positively correlated with "subjective" incentive pay plans such as "pay-for-knowledge" policies, and with the level of worker involvement in teams (high participation, line 3a). Finally, Milgrom and Roberts (1995) argue that problem-solving teams will be more effective when firms also provide employment security, job flexibility, training, and communication procedures. In our sample, work team variables, the employment security variable (line 4a), the high screening variable, various measures of labor-management communication (information sharing, line 7a; meet workers; meet union), and job flexibility (job rotation, line 5a) are highly correlated.[4]

This high degree of intercorrelation among HRM practices indicates that empirical models that estimate the impact of any one HRM practice on productivity will yield biased coefficients due to the omission of other HRM practices with which the one included practice is correlated. One possible solution to this omitted variable problem would be to enter the entire set of potentially important HRM variables into the productivity equations. This approach, however, is confounded by the severe collinearity among the HRM practices, making any one coefficient uninterpretable, and would not directly test whether combinations of HRM practices are the critical determinants of productivity.[5] To examine the importance of sets of highly correlated, and presumably complementary, HRM practices, one must examine the effects of interactions among the practices. There are an insufficient number of degrees of freedom to test a full set of interaction terms among all available HRM practice variables. And, an expansive set of interaction terms still would be confounded by collinearity among practices, so we seek to identify common clusters of practices.

A. *Identifying Systems of HRM Practices*

To summarize the overall HRM environments of the work sites in our sample, we identify the most common combinations of HRM practices in these production lines. Specifically, we examine an extensive set of variables that describe the seven HRM policy areas considered in the theories discussed in Section II: subjective and objective incentive compensation plans, extensive recruiting and selection, teamwork, employment security, job flexibility, training, and labor-management communication.[6] Combinations of practices that exist in our sample are referred to as "HRM systems."

Table 2 reports four distinctive combinations of HRM practices identified by inspection of the distributions of the HRM variables. These four HRM systems map out a hierarchy from most "traditional" to most "innovative."

- HRM System 4 is the traditional system. It contains no innovative practices. Facilities

[4] For the full set of correlations, see Ichniowski et al. (1995 pp. 13–15).

[5] Examining collinearity diagnostics (David A. Belsley et al., 1980) for our productivity model that includes all 15 HRM variables listed in Table 1 reveals a clear case of what Belsley et al. term "competing collinearity."

[6] To provide as rich a description as possible of the overall HRM environment, we use more variables than the 15 HRM practices in Table 1. We use from one to six specific practices describing each of the seven HRM policy areas. These other variables are dummies for intermediate levels of recruiting and screening activities; training in team problem-solving techniques and in statistical process control methods; the presence of informal work teams and local union support for team activities; employee participation in developing standard work practices; multiattribute gainsharing incentive plans; "pay-for-knowledge" salary plans; and combined operator job classifications and combined maintenance worker job classifications. In all, 26 HRM policy variables are used to classify the lines' HRM environments. Because we are classifying lines according to their work practices, this set of 26 variables does not include the union status or the grievance rate variables listed in Table 1.

TABLE 2—PROPORTION OF PRODUCTION LINES WITH SPECIFIC HRM PRACTICES WITHIN FOUR HRM SYSTEM CATEGORIES[a]

Practices in seven HRM policy areas[b]	HRM System 1	HRM System 2	HRM System 3	HRM System 4
1. *Incentive pay*				
a. Line incentives	1.00	0.31	0.00	0.00
2. *Recruiting and selection*				
a. High screening	1.00	0.15	0.00	0.00
3. *Teamwork*				
a. High participation	1.00	0.85	0.10	0.00
b. Multiple teams	1.00	0.62	0.00	0.00
c. Formal team practice	1.00	1.00	1.00	0.00
4. *Employment security*				
a. Employment security	1.00	0.23	0.48	0.00
5. *Flexible job assignment*				
a. Job rotation	1.00	0.15	0.03	0.00
6. *Skills training*				
a. High train	1.00	0.69	0.00	0.00
b. Low train	1.00	0.92	0.07	0.00
7. *Communication*				
a. Information sharing	1.00	0.54	0.62	0.00
b. Meet workers	1.00	0.77	0.72	0.00

[a] The sample for Table 2 is based on production lines and not production-line months. This sample includes 54 observations, and not just 36 production lines, because, for lines that switch HRM practices, it includes one observation for each different combination of HRM practices that the lines experience.
[b] See Table 1 for definitions of HRM variables.

with this system have close supervision by foremen; strict work rules and narrow job responsibilities; incentive pay based on quantity of output and not quality of output; no work teams; no practice of managers sharing financial information or meeting regularly off-line with workers; no screening; and no off-line or other formal training.

• HRM System 3 is similar to the System 4, except that these lines have introduced innovative practices in two specific areas. They have initiated worker involvement in teams (though few have a high level of involvement) and they have enhanced their labor-management communication practices, either by sharing financial information or through regular meetings between line managers and workers or their union representatives.

• HRM System 2 incorporates the information-sharing and work team practices associated with HRM System 3, but these lines also include two other innovative practices—extensive skills training and high levels of worker involvement in teams. While they may add one or two other innovative work practices, these lines always lack one or more of the following practices: extensive screening, job rotation or reduced job classifications, multiattribute incentive pay, or employment security.[7]

- HRM System 1 incorporates innovative HRM practices in all HRM policy areas. Lines with this system have a multiattribute incentive pay plan or a "pay-for-knowledge" incentive pay system; extensive screening of new workers, often lasting over one year; off-line training in technical skills and team problem solving; high levels of employee involvement in multiple problem-solving teams; job duties covering a wide range of tasks with workers often rotating across jobs; regular information sharing between workers and management; and an implicit employment security pledge.

In addition to identifying the common HRM systems by inspecting the distribution of HRM dummy variables in the sample, we also use three statistical procedures to identify common HRM systems. The alternative statistical classification procedures produce system classifications that overlap very closely with those system classifications described above, suggesting that the classification of lines' HRM environments is robust with respect to different classification procedures.[8] We will use the "systems" reported in Table 2 as the basic HRM measures in the productivity regressions, but also present regression results introducing HRM systems from one of the alternative classification procedures to illustrate the similarity of the results when HRM systems are measured with a different procedure.

B. *The Distribution and Average Productivities of HRM Systems*

Table 3 shows the distribution of the data and productivity means for the alternative HRM systems. While most lines do not change their HRM systems during the data period, 13.8 percent of the sample's 2,190 observations are from lines that change their HRM systems, moving from the more traditional Systems 4 and 3 to more innovative systems. However, no line adopted enough innovative practices to switch into HRM System 1. All HRM System 1 lines are new lines that began operations with the full complement of innovative practices listed in Table 2. No lines adopted less innovative systems.

Table 3 presents mean uptimes for lines with different HRM systems, differentiating between the uptime levels of "stayers" and "changers." The numbers along the diagonal of Table 3 show average uptimes for the "stayers," or for lines that did not change their HRM systems. According to the figures along the diagonal, these cross-sectional comparisons show productivity differentials relative to traditional HRM System 4 of 3.1 percentage points for HRM System 3; 2.5 percentage points for HRM System 2; and 4.1 percentage points for HRM System 1. The numbers in the area above the diagonal in Table 3 show uptime levels for "changers" before and after the adoption of more innovative HRM systems. The average longitudinal uptime gains for lines adopting more innovative systems of HRM practices range from 1 to 2.5 percentage points.

[7] A small number of lines have either high participation in teams or extensive training, but not both policies together. We classify these lines as HRM System 2 or 3, depending on how extensive the HRM practices in the other policy areas are. Our empirical results are virtually unaffected by how we categorize these few "intermediate" cases.

[8] Because HRM systems follow a hierarchy from a set of very traditional to more innovative practices, we use three scaling algorithms that create a single HRM "innovativeness" index. Two of these three scaling procedures, Nominate scaling and Guttman scaling, are described in Keith Poole and Howard Rosenthal (1991) and Edwin Ghiselli et al. (1981), respectively. The third scaling procedure is a simple 0-to-7 HRM index created by ranking the lines as "high" or "low" in the seven HRM policy areas and then adding up the number of "high" rankings. For each of the three HRM indices, we develop groupings of distinctive HRM environments by looking for natural breakpoints in the index. For further discussion of these classification procedures and of the estimated effects of these alternative HRM groupings on productivity, see Ichniowski et al. (1995 pp. 19–22). The four HRM systems developed from the Nominate classification procedure are introduced in the productivity regressions in Table 4.

TABLE 3—THE DISTRIBUTION OF SAMPLE OBSERVATIONS AND AVERAGE PRODUCTIVITIES BY HRM SYSTEM

	Ending HRM system			
Starting HRM system	HRM System 4	HRM System 3	HRM System 2	HRM System 1
HRM System 4	*Uptime in System 4* 0.899 (0.036) [N = 782]	*Uptime in System 3* 0.912 (0.039) *Prior uptime (Sys. 4)* 0.901 (0.034) [N = 172]	*Uptime in System 2* 0.939 (0.021) *Prior uptime (Sys. 3)* 0.912 (0.028) *Prior uptime (Sys. 4)* 0.894 (0.081) [N = 59]	—
HRM System 3	—	*Uptime in System 3* 0.930 (0.032) [N = 742]	*Uptime in System 2* 0.964 (0.011) *Prior uptime (Sys. 3)* 0.949 (0.027) [N = 82]	—
HRM System 2	—	—	*Uptime in System 2* 0.924 (0.070) [N = 287]	—
HRM System 1	—	—	—	*Uptime in System 1* 0.940 (0.041) [N = 77]

Note: Standard deviations are in parentheses ( ); sample size for cell is in brackets [ ].

IV. Econometric Specifications and Estimates

The uptime data displayed in Table 3 indicate that lines that upgrade their HRM system improve their uptime performance by 1 to 2 percentage points. These mean differences do not, however, control for many other factors that can affect uptime gains, and they do not compare the uptime gains for HRM "changers" to the uptime gains for those lines that did not change their HRM practices.[9] Furthermore, focusing exclusively on the uptime gains for changers makes no use of the information contained in the cross-sectional variation in uptime and HRM practices across lines. The primary objective of the econometric analysis below is to make the best use of both types of information—of the longitudinal and cross-sectional differences in uptime—and to compare the alternative longitudinal and cross-sectional estimators of the productivity effects of HRM policies.

[9] A comparison of the growth in uptime for HRM "changers" versus HRM "stayers" would correspond to the use of the "difference-in-differences" estimator used in program evaluation studies (Orley Ashenfelter and David Card, 1985; Robert J. LaLonde, 1986). Rather than present results using this estimator, we move directly to the fixed-effects estimator in Table 4, which is equivalent to difference-in-differences with added control variables. The significance of the control variables makes fixed-effects estimation more illuminating, and fixed-effects estimation is more readily applied to unbalanced monthly panel data.

TABLE 4—ESTIMATED PRODUCTIVITY EFFECTS OF HRM SYSTEMS IN OLS AND FIXED-EFFECTS MODELS (DEPENDENT VARIABLE: PERCENT UPTIME) [N = 2,190]

	OLS models without detailed technology controls[a]		OLS models with detailed technology controls[b]		Fixed effects models[c]	
HRM system	Classification of HRM systems from Table 2 (1a)	Classification of HRM systems from Nominate procedure (1b)	Classification of HRM systems from Table 2 (2a)	Classification of HRM systems from Nominate procedure (2b)	No controls for prechange productivity growth (3)	With controls for prechange productivity growth (4)
1. HRM System 1	0.097*** (0.007)	0.114*** (0.006)	0.067*** (0.007)	0.078*** (0.007)	—	—
2. HRM System 2	0.038*** (0.004)	0.057*** (0.004)	0.032*** (0.005)	0.041*** (0.005)	0.035*** (0.008)	0.068*** (0.019)
3. HRM System 3	0.011*** (0.002)	0.029*** (0.003)	0.014*** (0.003)	0.025*** (0.006)	0.025*** (0.006)	0.043*** (0.011)
R^2	0.246	0.283	0.409	0.409	0.066	0.068

[a] Control variables in columns (1a)–(1b) are: number of years line has been operating and years squared; year line was built and year built squared; dummy for start-up periods indicated by first 12 months of operations and 1-to-12 time trend for month of start-up operation; 1-to-5 index of quality of steel input; and number of annual eight-hour scheduled maintenance shifts.

[b] Control variables in columns (2a)–(2b) are: all controls listed in footnote a; dummy for type of customer; maximum speed of the line and speed squared; maximum width of the line and width squared; nine dummies to indicate specific pieces of equipment from start to finish of the line and a measure of the age of one piece of equipment at end of the line; a dummy to indicate high and low levels of computer control of line operations; and a variable to measure the value of major new equipment during its six-month installation period. For full set of coefficient estimates for the column (2b) model, see Appendix Table A1.

[c] Results for fixed-effects models are identical under different HRM classification procedures because all procedures identify the same lines as lines that switch HRM systems. There are no coefficient estimates for HRM System 1 in the fixed-effects model since no lines switched into this system. Other control variables in columns (3) and (4) are: age of line and age squared; dummy for start-up periods indicated by first 12 months of operations and 1-to-12 time trend for month of start-up operation; 1-to-5 index of quality of steel input; age of the end-of-the-line piece of equipment; and a variable to measure the value of major new equipment during its six-month installation period. For full set of coefficients for the column (3) model, see Appendix Table A1.

*** Significant at the 0.01 level.

To estimate the effects of HRM practices or systems of HRM practices on the uptime productivity measure, we begin with the following simple model of a line's uptime:

$$U_{it} = \boldsymbol{\gamma}'\mathbf{H}_{it} + \boldsymbol{\beta}'\mathbf{X}_{it} + e_{it}. \tag{3}$$

The determinants of productivity in (3) include dummy variables for the HRM systems ($\mathbf{H}_{it}$); line characteristics ($\mathbf{X}_{it}$), such as the technological features of the production process; and an error term that is temporarily assumed to be independently and identically distributed.

A. *The Productivity Effects of Alternative HRM Systems*

Table 4 contains the estimates of equation (3), introducing first a limited set and then an extensive set of technology controls to assess the sensitivity of the results to alternative specifications. Columns (1a)–(1b) of Table 4 report estimates of the effects of HRM systems in a model with a basic set of controls for technological determinants of line uptime. Results in column (1a) use the HRM classifications shown in Table 2 to identify the HRM systems, while those in column (1b) use the alternative Nominate statistical classification procedure to identify the HRM systems (see footnote 8). Columns (2a) and (2b) also report results for the two alternative HRM system definitions, but these specifications now introduce all 25 controls for differences in technology and other inputs.

These regression results reveal a hierarchical pattern in the productivity differentials of HRM systems: lines with HRM System 1 have the highest productivity, followed in order by lines with HRM Systems 2, 3, and 4. F-tests reveal that the difference between the coefficients on HRM Systems 1 and 2 and the difference between the coefficients on HRM Systems 2 and 3 are both significant at the 0.01 level in all models. The estimates of the productivity effects of HRM systems are very similar in the alternative specifications, although the addition of the detailed technology controls reduces the estimated impact of alternative HRM System 1 by some 3 percentage points.

B. *Fixed-Effects Estimates of the Productivity Effects of Alternative HRM Systems*

In estimating the impact of HRM systems on productivity, we want to avoid any possible selection bias arising from nonrandom selection of HRM practices. The ideal data set would be experimental data in which the selection of HRM practices is made randomly. However, without an experimental design that ensures random assignment, we must use our nonexperimental data to mimic the desired experimental comparison. In this section we present fixed-effects estimates in light of our concern with nonrandom selection issues.

The most likely reason for the nonrandom assignment of the innovative HRM practices versus the less innovative practices is that ''high-quality'' lines choose the most innovative practices. Thus, we introduce an unobserved line-specific quality variable, α_i, in our uptime regression.

$$(4) \qquad U_{it} = \boldsymbol{\gamma}'\mathbf{H}_{it} + \boldsymbol{\beta}'\mathbf{X}_{it} + \alpha_i + \varepsilon_{it}.$$

Estimates of γ in (3) above will be biased if the controls do not adequately incorporate line-specific determinants of productivity that are correlated with choice of HRM systems; that is, if $\alpha_i \neq 0$ and $E(\alpha_i \cdot \mathbf{H}_{it}) \neq 0$. For example, if the innovative HRM environment exists only in ''high-quality'' lines (or $H_{1it} = 1$ if $\alpha_i > \alpha_{\min}$, where $\alpha_{\min}$ is some threshold value of line quality), then estimates of γ are biased if α_i is omitted. Because the sample contains longitudinal data and information on lines that changed their HRM systems, we can control for this potential source of bias with a fixed-effects specification. This can be expressed as:

$$(5) \qquad (U_{it} - \bar{U}_{i\cdot}) = \boldsymbol{\gamma}'(\mathbf{H}_{it} - \bar{\mathbf{H}}_{i\cdot}) + \boldsymbol{\beta}'(\mathbf{X}_{it} - \bar{\mathbf{X}}_{i\cdot}) + (\varepsilon_{it} - \bar{\varepsilon}_{i\cdot}),$$

where the terms subscripted with $i\cdot$ indicate line-specific time-series means (for example, $\bar{U}_{i\cdot} = \Sigma_{j=1}^{T} U_{ij}/T$).

The fixed-effects results in column (3) of Table 4 eliminate the impact of all fixed line-specific effects (α_i) and also introduce controls for any time-varying productivity determinants that were included in the column (2) models. These results document positive effects from introducing more innovative HRM practices: relative to traditional System 4, lines adopting the System 2 set of practices gain 3.5 percentage points of uptime, and lines adopting System 3 practices gain 2.5 percentage points of uptime.[10]

C. *A Comparison of Fixed-Effects and Cross-Sectional Estimators*

The advantage of fixed-effects estimation is that it controls for any selection bias that would result if different quality lines adopt different HRM practices. The disadvantage of fixed-effects estimation is that it uses only the information from HRM ''changers'' in estimating the effects of HRM practices. All cross-sectional information is eliminated in the estimation. Recognizing that the information from HRM changers is limited because HRM changes are not common events, the data-collection protocol for this study was developed to obtain convincing cross-sectional productivity comparisons. First, we selected a specific production line that would be comparable across different companies. Second, during plant visits we reviewed features of each line with experienced engineers

[10] There is only one set of fixed-effects results because the different methods for measuring HRM systems identify the same set of lines as ''HRM system switchers.''

to identify technical sources of productivity variation. Finally, we collected the detailed vector of control variables described in Section I to account for the identifiable sources of productivity variation. If this vector of productivity controls, $\mathbf{X}_{it}$, successfully controls for the line-specific sources of productivity variation that are correlated with HRM choice, then the estimates of $\boldsymbol{\gamma}$ will not be biased by the omission of α_i in equation (3), and the coefficients in the fixed-effects results should be comparable to those in the cross-sectional results containing detailed capital controls.

The estimated productivity effects of HRM system variables in the fixed-effects model are virtually identical to those in the column (2b) specifications containing the detailed $\mathbf{X}_{it}$ controls. In particular, t-tests cannot reject the hypothesis that the coefficients on the HRM Systems 2 and 3 variables in the fixed-effects model are equal to the corresponding coefficients in the column (2b) model (see footnote 11). As shown in Table 3, no production line switches into HRM System 1, so the column (3) fixed-effects model contains no estimate of the effects of HRM System 1.

Additional specification tests provide further evidence that the column (2) OLS models already contain a thorough set of controls that adjust for line-specific determinants of productivity. Not only are the coefficients on the HRM system variables very similar between the fixed-effects and OLS specifications, but the coefficients on the control variables also are nearly equivalent between these two specifications.[11] The Appendix Table A1 reports the full set of coefficient estimates for both the column (2b) OLS specification and the fixed-effects specification.[12]

D. *Introducing Differential Productivity Growth Rates*

The fixed-effects estimators will be inconsistent if the adoption of innovative HRM practices is correlated with changes in productivity, such as declining productivity prior to adoption. For example, lines that experience a period of below-average productivity growth may be more likely to adopt new HRM practices. In this case, the estimate of $\boldsymbol{\gamma}$ in the equation (4) fixed-effects model would measure only the effects of adopting new HRM systems for those low-growth lines, and not the effects of new HRM systems for all lines. To control for this possibility, we expand the fixed-effects model to allow the growth rates in uptime to be different for lines that switch HRM systems:

$$(6)\quad (U_{it} - \bar{U}_{i\cdot}) = \boldsymbol{\gamma}'(\mathbf{H}_{it} - \bar{\mathbf{H}}_{i\cdot}) + \boldsymbol{\beta}'(\mathbf{X}_{it} - \bar{\mathbf{X}}_{i\cdot}) + \boldsymbol{\beta}^{c\prime}(\mathbf{X}^{c}_{it} - \bar{\mathbf{X}}^{c}_{i\cdot}) + (\varepsilon_{it} - \bar{\varepsilon}_{i\cdot}),$$

where the two variables in $\mathbf{X}^{c}_{it}$ are equal to the line age and line age-squared variables for changers measured prior to their HRM change, and are equal to zero at all other times. Thus, coefficient vector $\boldsymbol{\beta}^{c}$ represents the differential growth rate in productivity for changers, relative to the base-level productivity growth rate for nonchangers, in $\boldsymbol{\beta}$.[13] The results of esti-

[11] We calculate t-tests for the hypothesis that the coefficients on the $\mathbf{X}_{it}$ variables in the fixed-effects model are equivalent to the estimated coefficients in the cross-sectional model of column (2b). Each calculated t-test tests whether the difference in the estimated coefficients for the OLS and fixed-effects models is significantly different from zero, given the estimated variance-covariance matrices for these two models. We find that the coefficients on the two HRM variables in the fixed effects of column (3) are insignificantly different from their values in the OLS in column (2b), and five of the seven coefficients on the control variables in column (3) are insignificantly different from those in column (2b) at the 5-percent level.

[12] The coefficients on the control variables in OLS and fixed-effects models are all signed in the expected direction, indicating that lines have more delays with less scheduled maintenance; lower quality steel input; older technologies; start-up periods for brand new lines; the introduction of new pieces of equipment; and higher line speeds.

[13] Equation (6) controls for systematic differences between the average growth rate in uptime for all lines and the growth rate in uptime among HRM switchers over the entire prechange period. An alternative model permits the adoption of a new HRM system to be a function of short-term declines in productivity just prior to adoption. If we reestimate the fixed-effect model and drop an equal number of months before and after the HRM system changes,

mating equation (6) are in column (4) of Table 4. The coefficients for this augmented fixed-effects model show somewhat larger effects of changing to HRM System 3 or HRM System 2 than in the column (3) model, indicating that lines that switched their HRM systems had somewhat lower productivity growth than average in the periods prior to the adoption of the new HRM systems.[14]

Note finally that the standard errors on HRM coefficients may be underestimated due to serially correlated errors. We allow for the possibility of first-order serial correlation of the errors in equation (4) (or $\varepsilon_{it} = \rho\varepsilon_{i(t-1)} + \upsilon_{it}$) and for first-order serial correlation in the fixed-effects models. When all the models in Table 4 were reestimated allowing for first-order serial correlation, the estimated standard errors increased only slightly. The magnitudes and levels of significance of all estimated effects of the HRM system variables virtually are identical to those presented in Table 4.[15]

E. *The Magnitudes of the Estimated Productivity Effects of HRM Systems*

The magnitudes of the estimated effects of HRM systems on uptime are quite consistent across specifications in Table 4. The baseline fixed-effects model in column (3) reports uptime differentials of 2.5 percentage points for HRM System 3 and 3.5 percentage points for HRM System 2, and the estimates from the OLS models with detailed technology controls in column (2) are insignificantly different from these fixed-effects estimates. While fixed-effects estimates for the productivity differentials for HRM System 1 could not be calculated, the most conservative estimate of the productivity differential for HRM System 1 in any OLS model in Table 4 is 6.7 percentage points. Are uptime differentials of this magnitude economically important?

Using cost data from one small-scale line, we calculate that a conservative estimate of the effect of a 1-percentage-point increase in uptime on revenues net of any differences in production cost and any differences in the direct costs of the HRM policies would be approximately \$27,900 per month.[16] Using this value,

estimates will not be biased by differences in uptime growth even with serial correlation in the errors (Ashenfelter and Card, 1985 p. 652). We reestimate the model deleting observations for one or two quarters before and after any changes in HRM systems, and the results virtually are the same as those reported in column (3) of Table 4. We suspect that changes in uptime over such short periods would not cause management to adopt new work policies, so we focus on the possibility of longer-term declines in productivity growth.

[14] We find evidence of a very modest three-month lag in the OLS and fixed-effects uptime models. For example, when the fixed-effects uptime regression [Table 4, column (3)] is reestimated with a lag of three months introduced in the HRM system variables, their coefficients rise by about 0.005 (e.g., from 0.025 to 0.030 for HRM System 3). These lagged HRM variables provide a slightly better description of the changes in productivity due to the new HRM practices than do the concurrent values of the HRM systems. In the fixed-effects model, an F-test reveals that the three-month lags in HRM Systems 2 and 3 add explanatory power to the uptime model already containing the concurrent HRM system variables ($F[2,2065] = 3.64$), whereas the converse test concerning the addition of concurrent HRM system variables to a model that has the lagged HRM variables is insignificant ($F[2,2065] = 1.17$).

[15] A further consideration in estimating the productivity models is that the percent uptime variable is bounded by zero and one, suggesting the possibility of Tobit estimation. We do not pursue Tobit estimation for the fixed-effects models because the coefficient estimates of fixed-effects Tobit models are not consistent: the nonlinearity of the Tobit model introduces an incidental parameters problem. However, when the OLS models are estimated as a Tobit with a mass point at one, the estimated coefficients essentially are the same as the OLS estimates presented in Table 4. Note that no lines have uptimes at the mass point of one. A double-sided Tobit with a second mass point at zero is unnecessary since no lines have uptimes close to zero.

[16] During a delay, a line loses revenue from planned output, incurs fixed costs (which exceed \$5000 per *hour* in some lines) and some "variable" costs such as labor costs, but saves on other variable costs such as the costs of steel and energy inputs. Using a conservative estimate of the profit margin on a ton of steel and liberal estimates of the costs that would not be incurred during a delay, we calculate an increase of \$30,000 per month in operating income from a 1-percent increase in uptime. We then subtract \$2,100 from this figure for the costs of the new HRM policies. We calculate this estimate by using information from interviews to compare the costs of policies in HRM System 1 and HRM System 4. Higher costs of HRM System 1 are due to the time production workers must meet off the line, additional HRM staff, consultants for ongoing training and team organization, certain fixed costs of

we conservatively estimate that when one line in our sample changed from HRM System 4 to HRM System 2 and maintained these changes for ten years, it increased its operating profits by well over $10 million dollars strictly as a result of the HRM changes.[17]

V. Alternative Explanations

The regression coefficients displayed in Table 4 imply that introducing innovative HRM systems increases workers' productivity. However, other factors that change over time within lines, such as changes in plant management or threats of job loss, could be the true cause of the productivity increases. In this section, we estimate alternative specifications that consider these factors.

A. *Management Quality*

If better managers are more likely to adopt innovative HRM systems and to adopt other productivity-enhancing practices at the same time, the estimated HRM effects will suffer from omitted variable bias. We collected additional data to provide two tests of this hypothesis. First, we reestimate the fixed-effects model in Table 4, column (3), and include several standard measures of managerial quality—the tenure of the line manager, the tenure of the site's HR manager, and the squares of these tenure variables. We also include two dummies for whether the line has a new line manager or a new HR manager, because the estimated effects of switching HRM systems may only reflect the effects of newly hired managers who change HRM policies upon their arrival. The inclusion of these variables [Table 5, column (2)] produces virtually no change in the estimated HRM system coefficients relative to our base-model estimates [Table 5, column (1)]. Though only the fixed-effects results are reported in Table 5, results for the OLS model with detailed controls are essentially equivalent to these results for all specifications displayed in Table 5.

These measures of managerial quality may be incomplete if, for example, "good" managers adopt innovative HRM practices and also make other changes to achieve superior productivity. We therefore include in the fixed-effects model 72 person-specific management dummies—one dummy for each period that a line's operations manager and HR manager remained unchanged. As shown in column (3) of Table 5, the inclusion of this vector of person-specific management dummies increases the estimated effects of HRM Systems 2 and 3 compared to the estimates from the baseline fixed-effects model in column (1) of Table 5. Overall, the results indicate that the effects of the HRM system variables are independent of any managerial behaviors or philosophies that are specific to any individual manager. While higher-quality managers may eventually choose to adopt innovative HRM practices, the productivity effects that arise are from the changes in the practices, not from the inherent quality of the manager.

B. *Threat Effects*

Some lines may face serious threats of layoffs and plant shutdowns, and these threats

developing these policies, and costs of employment security for wages paid for idle time (assuming that a line would be idle for two months every four years). We allow HRM System 1 to save on the salary of one foreman. Assuming a relatively short time horizon of five years for amortizing fixed costs, the monthly difference in costs between HRM Systems 4 and 1 is about $2,100 per percentage-point gain in uptime. The $27,900 estimate of the monthly revenue increase net of the costs of HRM policies probably is an underestimate because larger-scale lines will have bigger revenue effects, and increases in output quality (discussed in Section V below) yield further revenue increases.

[17] Uptime at this line was consistently some 8 percentage points higher after the change in HRM systems. The Table 4, column (3), fixed-effects model indicates that 3.5 percentage points of this gain can be attributed to the new HRM practices themselves. Uptime also increased at this line because it began using higher quality steel input near the time of the HRM changes (see Appendix Table A1, column 2, line 5). At $27,900 per percentage point per month, the 3.5-point increase in uptime implies a $1,171,800 annual increase in operating profits and a $12,889,800 increase (without discounting) over the 11 years that this line sustained the improved performance under the new HRM system. Even if this line operated 20 percent below capacity during this period, the change in operating income from a 3.5-percentage-point increase in uptime over an 11-year period still would exceed $10 million. Increases in output quality after this line changed its HRM system further magnify the value of the more progressive HRM systems.

TABLE 5—ESTIMATED PRODUCTIVITY EFFECTS OF HRM SYSTEMS IN FIXED-EFFECTS MODELS WITH CONTROLS FOR TIME-VARYING DETERMINANTS OF PRODUCTIVITY
(DEPENDENT VARIABLE: PERCENT UPTIME)
[$N = 2{,}190$]

HRM system	(1)	(2)	(3)	(4)	(5)	(6)
1. HRM System 2	0.035*** (0.008)	0.046*** (0.009)	0.064*** (0.012)	0.034*** (0.009)	0.034*** (0.009)	0.052*** (0.014)
2. HRM System 3	0.025*** (0.006)	0.026*** (0.006)	0.048*** (0.010)	0.025*** (0.006)	0.025*** (0.006)	0.044*** (0.011)
Time-varying controls						
3a. Technology controls[a]	Yes	Yes	Yes	Yes	Yes	Yes
3b. Management tenure variables[b]	No	Yes	No	No	No	Yes
3c. Manager-specific dummy variables[c]	No	No	Yes	No	No	Yes
3d. Shutdown threat variables[d]	No	No	No	Yes	No	Yes
3e. Year dummy variables	No	No	No	No	Yes	Yes
F tests[e]		F(6,2175) = 9.074	F(72,2109) = 3.95	F(2,2174) = 7.27	F(13,2171) = 5.93	F(93,2088) = 4.03
R^2	0.066	0.090	0.176	0.072	0.099	0.199

[a] The technology variables are listed in footnote c to Table 4 [the Table 5, column (1), model replicates the Table 4, column (3), model].
[b] The management tenure variables are the tenures of the HR and line managers (and squared terms) and dummy variables for tenure less than three years for those managers.
[c] The management-specific dummy variables are 72 dummy variables equal to one for each specific HR manager and line manager team in place.
[d] The threat variables are the percent of the plant permanently shut down and a dummy for the recent use of layoffs.
[e] The F-tests test the joint null hypothesis that the variables added in that column have coefficients that are significantly different from zero.
*** Significant at the 0.01 level.

may cause employees to work harder. If ''threatened'' lines also are more likely to adopt new HRM systems, the coefficient on the HRM systems will pick up omitted threat effects. Interviews at some sites suggest that partial plant shutdowns were an important part of the impetus for workers and managers to agree to adopt new work practices. To test the possibility that the HRM variables serve as proxies for threat effects, we create two variables measuring threat effects: the percentage of the site's operations that are permanently shut down and a dummy variable equal to one when the line has a recent history of layoffs. Inclusion of these two variables in the fixed-effects model has little effect on the estimated HRM system coefficients as shown in column (4) of Table 5.

While threat effects may have helped convince labor and management at certain sites to agree to new work practices, these threat variables do not account for the estimated effects of HRM practices on productivity for several reasons. First, not all threatened lines changed their HRM practices, so threat alone cannot explain HRM effects. Second, even in lines where threats of closure occurred along with the changes in HRM practices, these lines have sustained increases in uptime long after the threat of closure has dissipated. Third, innovative HRM practices are widely adopted by new lines that have no threat of closure, and the practices are associated with success in these lines as well.

C. *Worker's Pay*

Another possibility is that workers in lines with the more innovative HRM systems may be working more productively because they are paid more. To test this hypothesis, we collected wage data from company records and from union contracts (1989 to 1993) and coupled these data with interview information to estimate average pay rates.[18] When we include wage rate data, the sample size falls to 863, since the sample is limited to recent time periods. The uptime model is reestimated for this sample with and without the average wage of production workers. The coefficient on the average wage is insignificant in all OLS and fixed-effects models and, therefore, there are no changes in the coefficients on the HRM variables when the wage variable is introduced.[19] Factors that are exogenous to the current productivity of the finishing lines determine wages.[20]

[18] The average wage data for production workers include incentive pay, overtime pay, shift pay, and profit sharing. When these averages were not available for the production line, we used the union labor contracts to predict average wages, combined with interview information on the average grade level, average amount of overtime, and average incentive pay percentages (including profit sharing). Only two lines were unable to provide data for the calculation of average wages. Fringe benefit compensation is omitted, and though it is slightly higher in unionized lines than nonunion lines due to higher pensions and days off, this omission does not appear to affect the results. First, wages continue to be insignificant determinants of uptime when the sample is restricted to unionized lines. Second, union-nonunion differences in fringe benefits do not change with the timing of "HRM changers," and wages continue to have no effects on uptime in fixed-effects models.

[19] The coefficients (standard errors) on the wage variable are 0.00016 (0.00079) for the OLS model with detailed controls and 0.00168 (0.00172) for the fixed-effects model. The coefficients on the HRM variables for the subsample having wage data (N = 863) are slightly smaller in magnitude than in the full sample, but they remain significantly different from zero. These results are unchanged when real wages replace nominal wages.

[20] Insignificant wage effects are not surprising. First, wage variation in the sample is small. Second, wage changes typically occur when national labor agreements are renegotiated, and these periods do not coincide with systematic changes in productivity. Third, wage changes also do not coincide with changes in HRM systems, so inclusion of the wage variable does not affect the estimated effects of HRM systems in fixed-effects uptime models.

D. *Other Time-Varying Determinants of Productivity*

Finally, we reestimate the fixed-effects specification including a set of year dummies that may be correlated with any omitted time-varying determinants of productivity. Table 5, column (5), reports results from this model. Although the year dummies show a pattern of increasing productivity over time, the effects of HRM System 2 and HRM System 3 are again almost identical to the corresponding coefficients in the baseline fixed-effects specification in column (1). Column (6) reports estimated coefficients on the HRM system variables when the fixed-effect model includes year dummies and controls for all other time-varying variables considered in Table 5. The estimated coefficients for the HRM Systems 2 and 3 variables now are somewhat larger than they were in the baseline fixed-effects model of column (1).

In sum, the Table 5 results do not provide any evidence that the coefficients on HRM system variables are biased upward by omitted line-specific or time-varying factors.

E. *Effects of HRM Systems on Product Quality*

The evidence shows positive significant effects of HRM systems, but the value of these productivity effects will be diminished if they are achieved at the expense of reductions in the quality of output. We collected data on output quality as measured by the lines' monthly "prime-yield" rates—the percent of total production that met the standards for designation as "prime" finished steel. With these data, we are able to test whether the uptime gains reported in Tables 4 and 5 are offset by any decreases in the quality of steel production under the more innovative HRM systems.

Table 6 presents estimates of the effects of HRM systems on prime-yield rates[21] in mod-

[21] Because total steel production is the denominator of the prime-yield rate variable, these estimates are not affected by any effects of the HRM system variables on production and line delays.

TABLE 6—ESTIMATED EFFECTS OF HRM SYSTEMS ON QUALITY OF PRODUCTION IN OLS AND FIXED-EFFECTS MODELS
(DEPENDENT VARIABLE: PERCENT PRIME YIELD)
[N = 1,750]

	OLS models without detailed machinery controls[a]	OLS models with detailed machinery controls[b]	Fixed-effects models[c]
HRM measure	(1)	(2)	(3)
1a. HRM System 1	0.152*** (0.008)	0.132*** (0.009)	—
1b. HRM System 2	0.098*** (0.005)	0.046*** (0.007)	0.036*** (0.007)
1c. HRM System 3	0.064*** (0.004)	0.044*** (0.005)	0.050*** (0.005)

[a] Control variables in column (1) are: number of years line has been operating and years squared; year line was built and year built squared; dummy for start-up periods indicated by first 12 months of operations and 1-to-12 time trend for month of start-up operation; 1-to-5 index of quality of steel input; number of annual eight-hour scheduled maintenance shifts; and four dummies for slight differences in how prime yield is measured in different lines.

[b] Control variables in column (2) are: all controls listed in footnote a; dummy for type of customer; maximum speed of the line and speed squared; maximum width of the line and width squared; nine dummies to indicate specific pieces of equipment from start to finish of the line and a measure of the age of one piece of equipment at end of the line; a dummy to indicate high and low levels of computer control of line operations; a variable to measure the value of major new equipment during its six-month installation period; and four dummies for slight differences in how prime yield is measured in different lines.

[c] Control variables in column (3) are: age of line and age squared; dummy for start-up periods indicated by first 12 months of operations and 1-to-12 time trend for month of start-up operation; 1-to-5 index of quality of steel input; age of the end-of-the-line piece of equipment; and a variable to measure the value of major new equipment during its six-month installation period.

*** Significant at the 0.01 level.

els that include controls for steel input quality, capital vintage, machinery, scheduled maintenance, and other controls included in the uptime equations.[22] The same hierarchical pattern observed in the uptime models in Tables 4 and 5 is evident in the prime-yield models in Table 6. Lines with HRM System 1 have prime-yield rates that considerably exceed the yields of lines with other HRM systems. HRM Systems 2 and 3 produce comparable gains in prime-yield rates relative to HRM System 4. Fixed-effects results also demonstrate higher yield rates under more innovative HRM practices.[23]

[22] To account for slight differences in the way prime yield is measured from line to line, we include in the prime-yield regressions additional controls not included in the uptime regressions. Prime-yield models in Table 6 include four dummy variables for the five slightly different ways that prime yield is calculated at different lines. For example, prime steel production might be expressed as a percentage of total tons of steel at the exit end of the finishing line or as a percentage of total tons of steel input on the entry end of the line. These dummy variables in OLS specifications are consistently significant with the expected signs given the differences in the definitions. The definitions the lines used to calculate prime yield do not change over time, and so these variables drop out of the fixed-effects models.

[23] The prime-yield regressions in OLS and fixed-effects models were reestimated with corrections for first-order serial correlation. Standard errors in these models were only slightly larger than those in the Table 6 models. Magnitudes and levels of significance of HRM system coefficients are very similar to those reported in Table 6.

F. *Why Don't All Lines Have the High-Productivity HRM Systems?*

Based on the relative stability of the coefficients in the productivity regressions in Tables 4 and 5, we conclude that the estimated productivity effects of innovative HRM systems are largely independent of the adoption propensity. However, this conclusion would even be more persuasive if we could identify likely reasons why some lines adopt the productivity-enhancing HRM systems and others do not.

There are two obvious explanations for the limited adoption: (1) managers have had only limited knowledge about the performance effects of HRM systems; and (2) nonpecuniary barriers to change beyond the direct costs of the work practices limit adoption in certain lines. During our fieldwork at the finishing lines, we found support for both of these explanations.

When most steel mills were built, innovative practices were not in use. However, recently opened lines at "greenfield" sites, as well as older lines that had been closed but were opened with new owners and workers, are adopting innovative work practices. Knowledge about the potential productivity gains of innovative practices can be considered to be analogous to knowledge about the effects of a technological innovation. While mills at many companies now have some experience with new work practices, many mills still have not adopted the productivity-improving innovation. In particular, continuously operating lines at "brownfield" sites are still much more likely to have traditional HRM practices.

Our field interviews revealed two sets of reasons for the resistance to the new practices in the older lines despite the growing knowledge about the productivity benefits of new work practices. First, managers and production workers at these sites have invested in skills and work relationships that would have to change substantially if new HRM systems were adopted. These costs of changing HRM practices do not exist in new lines or in old lines that are reopened by new owners.[24] Second, the old continuously operating lines are marked by greater mistrust between labor and management, and these lines must overcome this mistrust before the new work practices can be effective.[25] The very fact that all of our "greenfield" lines adopted innovative practices suggests that it is the transition costs of adoption that have limited adoption rates.

Different rates of adoption across lines, therefore, are a function of differences in these nonpecuniary costs of adoption that affect the profitability of the practices, and not differences in expected productivity gains. In some older lines, new managers or certain workers can champion the new work practices and overcome these impediments to change. In others, credible threats of plant closure motivate existing workers and managers to adopt more productive work arrangements. At the same time, factors like threat effects or workers who champion new practices do not appear to be systematic determinants of the productivity effects of innovative HRM practices. When old lines do overcome these nonpecuniary costs of switching policies, they experience significant productivity gains from the innovative policies. The variation across lines and within lines over time in these nonpecuniary costs of adopting new work practices

[24] At the same time, the age and older technology of these lines are not responsible for the limited adoption of new work practices. Detailed controls in the productivity models for capital vintage do not eliminate the productivity effects of HRM systems for several reasons. When older lines in the sample were shut down and later reopened by new owners, all adopted many new work practices. And, as illustrated by the results of the fixed-effects models, some continuously operating older lines adopted new HRM systems that raised their productivity.

[25] Labor-management trust is needed for many innovative HRM practices to be effective (Baker et al., 1994). Our interviews revealed how a low level of labor-management trust in older lines rendered ineffective new work practices like information sharing, productivity-improvement teams, and employment security. For example, the manager at one older line observed: "It's just difficult to change attitudes in old plants with a history of tension and mistrust. We now share financial information with workers, but some workers still believe there are two sets of books." At another line, a supervisor stated: "Workers out here don't believe that they have employment security ... Since employment security is only a contractual guarantee, they know that it may very well go away in the next [union] contract."

allows us to observe the different work practices in this technologically homogeneous sample, and thus to estimate the impact of alternative HRM practices on productivity.

VI. Productivity Effects of Individual HRM Practices

Tables 4–6 show significant positive effects of innovative systems of HRM practices on productivity and product quality. These models do not, however, compare the effects of individual HRM practices to those of systems of practices and, therefore, do not provide evidence on whether the individual work practices that comprise an HRM system are complementary. Complementarity among work practices implies that the magnitude of the productivity effect of the system of HRM policies is larger than the sum of the marginal effects from adopting each practice.

In Table 7 we compare the productivity effects of HRM systems with the productivity effects of individual work practices. When variables for individual HRM practices are added to the regressions containing HRM system dummies, the individual practices have no additional impact on productivity. In other words, the HRM system dummies capture the full productivity impact of the lines' HRM environments; the estimated effect of any individual HRM practice essentially is zero. Specifically, columns (1a)–(1d) show results from 15 separate productivity models that are the same as the OLS model in Table 4, column (2b), except that each model also includes one additional variable which measures an individual work practice. Similarly, columns (2a)–(2c) show results from models which replicate the Table 4, column (3), fixed-effects model, but each model in these columns also includes one additional variable for an individual HRM practice.[26] In nearly all models in the columns (1a)–(1d) OLS models and in the columns (2a)–(2c) fixed-effects models, the coefficients on the variables measuring individual work practices are insignificant.[27]

Columns (3) and (4) of Table 7 report results from productivity models that introduce only the individual HRM practices without the HRM system variables. The coefficients on the individual practice variables in the OLS and fixed-effects models without the HRM system dummies are positive and significant with magnitudes ranging from about 1 to 3 percentage points.[28] A comparison of the OLS coefficients in column (1d) with those in column (3) and a comparison of the fixed-effects coefficients in column (2c) with those in column (4) show that the effects of the individual HRM practices in models without the HRM system dummies disappear once the HRM sys-

[26] All OLS and fixed-effects models in Table 7 were reestimated with corrections for first-order serial correlation. Again, the magnitudes of all coefficients virtually are unaffected by this correction. Standard errors for some coefficients increase, but only slightly. The significance levels of all HRM coefficients are similar in all cases to those shown in Table 7.

[27] While the work practices employed by lines with a given HRM system are highly similar, some work practices do vary within HRM System 3 lines and within the HRM System 2 lines (see Table 2). Furthermore, in addition to the lines that changed enough practices to "switch systems" (see Table 3), other lines change individual HRM policies during the data period. The coefficients on the variables which measure individual HRM practices in the OLS estimates shown in column (1d) are positive and significant in only two cases (profit sharing in line 1 and low train in line 10), where the effects still are very modest. As in Table 4, the HRM System 1 variable could not be included in fixed-effects models since no line switched into this category with the most innovative HRM practices. Also, some fixed-effects models of the effects of individual HRM practices could not be estimated because certain individual HRM policies do not change in any lines in the sample period. In the fixed-effects models which include the HRM system variables [columns (2a)–(2c)], the only coefficient which is significantly positive for an individual HRM variable is the coefficient on the low grievance variable (line 15), suggesting that productivity-enhancing changes in HRM systems are accompanied by a movement to an environment with little grievance activity, consistent with studies that have found an inverse relationship between grievance activity and productivity (Ichniowski, 1986).

[28] Fixed-effects models which include the multiple teams (line 6) and information-sharing (line 11) variables could be estimated in column (4) models without the HRM system dummies because these variables change over time within some lines. However, within-line changes in these two variables are collinear with switches between certain HRM systems, and so the two corresponding fixed-effects models in columns (2a)–(2c) could not be estimated.

TABLE 7—ESTIMATED PRODUCTIVITY EFFECTS OF HRM SYSTEMS AND INDIVIDUAL HRM PRACTICES (DEPENDENT VARIABLE: PERCENT UPTIME) [N = 2,190[a]]

	OLS models with HRM system variables and with individual HRM practice variable[b]				Fixed-effects models with HRM system variables and with individual HRM practice variable[c,d]			OLS models with only individual HRM practice[b]	Fixed-effects models with only individual HRM practice[c]
Individual HRM practice included in models in the row	Coef. on HRM System 1 (1a)	Coef. on HRM System 2 (1b)	Coef. on HRM System 3 (1c)	Coef. on individual HRM practice (1d)	Coef. on HRM System 2 (2a)	Coef. on HRM System 3 (2b)	Coef. on individual HRM practice (2c)	Coef. on individual HRM practice (3)	Coef. on individual HRM practice (4)
1. Profit sharing	0.066*** (0.007)	0.026*** (0.005)	0.012*** (0.003)	0.006** (0.003)	—	—	—	0.007** (0.002)	—
2. Line incentives	0.068*** (0.007)	0.032*** (0.005)	0.014*** (0.003)	−0.002 (0.004)	0.031*** (0.009)	0.023*** (0.006)	0.007 (0.005)	0.012*** (0.004)	0.012*** (0.004)
3. High screening	0.068*** (0.015)	0.032*** (0.005)	0.013*** (0.003)	−0.001 (0.001)	—	—	—	0.029*** (0.004)	—
4. High participation	0.095*** (0.009)	0.052*** (0.006)	0.019*** (0.004)	−0.023** (0.004)	0.058*** (0.010)	0.028*** (0.006)	−0.024*** (0.006)	0.005* (0.003)	−0.008* (0.005)
5. Formal team practice	0.062*** (0.008)	0.027*** (0.006)	0.012*** (0.004)	0.004 (0.003)	0.034*** (0.013)	0.025*** (0.008)	0.001 (0.006)	0.014*** (0.003)	0.011*** (0.004)
6. Multiple teams	0.060*** (0.011)	0.026*** (0.008)	0.014*** (0.009)	0.008 (0.009)	—	—	—	0.026*** (0.004)	0.010* (0.006)
7. Employment security	0.047*** (0.010)	0.023*** (0.005)	0.008** (0.004)	0.011 (0.004)	—	—	—	0.025*** (0.003)	—
8. Job rotation	0.084*** (0.009)	0.033*** (0.005)	0.018*** (0.004)	−0.021*** (0.006)	—	—	—	0.010** (0.005)	—
9. High train	0.068*** (0.008)	0.033*** (0.006)	0.014*** (0.003)	−0.003 (0.006)	0.037*** (0.009)	0.025*** (0.006)	−0.006 (0.007)	0.016*** (0.004)	0.001 (0.007)
10. Low train	0.054*** (0.009)	0.021*** (0.007)	0.013*** (0.003)	0.013** (0.006)	0.028*** (0.010)	0.023*** (0.006)	0.008 (0.006)	0.026*** (0.004)	0.015*** (0.005)
11. Information sharing	0.077*** (0.011)	0.038*** (0.007)	0.017*** (0.004)	−0.004 (0.003)	—	—	—	0.013*** (0.002)	0.010* (0.006)
12. Meet workers	0.060*** (0.008)	0.028*** (0.005)	0.012*** (0.004)	0.005 (0.004)	0.028*** (0.010)	0.024*** (0.006)	0.007 (0.006)	0.021*** (0.003)	0.012*** (0.004)
13. Meet union	0.067*** (0.010)	0.032*** (0.006)	0.014*** (0.004)	0.00003 (0.004)	0.031*** (0.009)	0.025*** (0.006)	0.014 (0.014)	0.017*** (0.003)	0.024** (0.012)
14. Union	0.073*** (0.008)	0.037*** (0.006)	0.016*** (0.004)	0.012 (0.008)	—	—	—	−0.026*** (0.007)	—
15. Low grievance	0.066*** (0.008)	0.031*** (0.005)	0.014*** (0.004)	0.0003 (0.003)	0.013 (0.013)	0.008 (0.010)	0.022** (0.010)	0.012*** (0.003)	0.029*** (0.006)

Notes: To interpret this table, note that each row represents up to four regressions. For example, in row 2 the coefficients in columns (1a)–(1d) are from one OLS regression containing three system variables and one individual practice variable (for line incentives); the coefficients in columns (2a)–(2c) are from the comparable fixed-effects regression; the coefficient in column (3) is from the OLS regression containing the one practice variable (line incentives) and no system variables; and the coefficient in column (4) is the fixed-effects estimate comparable to column (3).

[a] Standard errors reported in parentheses.

[b] Other control variables included in the OLS models are those listed in footnote b to Table 4.

[c] Other control variables in the fixed-effects models are those listed in footnote c to Table 4.

[d] No line switches into HRM System 1 and so the coefficient on HRM System 1 is not estimated in fixed-effects models.

* Significant at the 0.10 level. ** Significant at the 0.05 level. *** Significant at the 0.01 level.

tem variables also are included. These results from Table 7 demonstrate that the apparent positive effects of individual practices in models without controls for HRM systems are biased by the omission of other HRM practices with which the one included practice is correlated. New work practices (such as work teams, quality circles, job rotation, or information sharing) are often introduced together as part of a coherent system of practices; thus, the productivity effects of individual practices cannot be readily isolated.[29]

To provide further evidence about the possible complementarity of HRM practices, we test whether the interactions among HRM practices that are measured implicitly by the four HRM system dummies are significant when they are added to a regression containing dummies for all the individual practices. Specifically, we reestimate the OLS model corresponding to the Table 4, column (2b), model, but we include dummies for all individual HRM policies in addition to the HRM system dummies. An F-test rejects the hypothesis that the HRM system variables add no explanatory power to the model that already includes all individual HRM policies entered separately ($F[3,2134] = 7.62$). Similarly, when we reestimate the Table 4, column (3), fixed-effects model but include dummy variables for each of the individual HRM policies that change over time in the sample period, an F-test rejects the hypothesis that the HRM systems variables add no explanatory power to the model ($F[2,2142] = 5.40$).

The evidence shows that *systems of HRM practices determine productivity and quality, while marginal changes in individual work practices have little effect.* The preponderance of evidence in this study also is consistent with the conclusion that complementarities among innovative work practices are important. Note first that the positive correlations among innovative HRM practices show that firms are likely to select multiple innovative practices rather than single practices, suggestive of complementarities among policies. Second, the productivity regressions reenforce the view that complementarities are important, even though the collinearity among practices inherently limits our ability to distinguish between the impact of individual practices and the impact of systems of practices. HRM system variables are shown to raise productivity substantially, and the effects of these system variables exceed the effects of the full set of individual practices. Third, in extensive interviews during our plant visits, operations managers offered numerous explanations as to why practices that are introduced in isolation have little effect on performance (Ichniowski et al., 1995 pp. 36–37). Finally, as described in Section V, subsection F, growing knowledge of the effectiveness of sets of innovative work practices has led steel companies to adopt these practices in all ''greenfield'' sites, while high transition costs of adopting entirely new systems of work practices have slowed their introduction at ''brownfield'' sites.

VII. Conclusion

This paper presents new evidence on the productivity effects of employment practices. The evidence, derived from unique monthly panel data on productivity and HRM practices in a homogeneous sample of production lines, shows that innovative HRM practices raise worker productivity. Moreover, systems of innovative HRM practices have large effects on production workers' performance, while changes in individual employment practices have little or no effect. Thus, the preponderance of the evidence suggests that, in these steel finishing lines, innovative employment practices tend to be complements, as is proposed in the recent theoretical work on optimal incentive structures. That is, workers' performance is substantially better under incentive pay plans that are coupled with supporting innovative

[29] The estimated negative coefficient on union status in the OLS model without the HRM system dummies [Table 7, column (3), line 14] also reflects the more complex dynamics of how systems of HRM policies determine productivity. On average, union lines are less productive than nonunion lines in our sample. But not all union lines are less productive than the nonunion lines in the sample. The negative union coefficient in Table 7, column (3), line 14, reflects the fact that a large number of union lines have the low productivity practices of HRM Systems 3 and 4, even though the lines in the most productive HRM System 1 are unionized lines. Once the productivity models control for the effect of HRM systems in columns (1a)–(1d), the union productivity effect becomes insignificant.

work practices—such as flexible job design, employee participation in problem-solving teams, training to provide workers with multiple skills, extensive screening and communication, and employment security—than it is under more traditional work practices.

Appendix

Table A1—Full Set of Coefficient Estimates OLS and Fixed-Effects Uptime Models [for Columns (2B) and (3) of Table 4]

Variable	OLS model with detailed controls	Fixed-effects model
1a. HRM System 1	0.078***	—
	(0.007)	
1b. HRM System 2	0.041***	0.035***
	(0.005)	(0.008)
1c. HRM System 3	0.025***	0.025***
	(0.003)	(0.006)
2. Maintenance shifts per year	0.0002***	—
	(0.00004)	
3. Index of steel input quality	0.008***	0.005**
	(0.002)	(0.002)
4a. Year built	0.018***	—
	(0.003)	
4b. (Year built)^2	−0.0001***	—
	(0.00002)	
5a. Line age	0.0102***	0.011***
	(0.0011)	(0.001)
5b. (Line age)^2	−0.0002***	−0.0002***
	(0.00002)	(0.00002)
6a. Dummy for start-up period	−0.043**	−0.071***
	(0.011)	(0.017)
6b. Time trend for start-up period	0.004**	0.004**
	(0.001)	(0.002)
7a. Equipment dummy 1a	0.032***	—
	(0.004)	
7b. Equipment dummy 1b	0.019***	—
	(0.003)	
8a. Equipment dummy 2a	−0.043***	—
	(0.005)	
8b. Equipment dummy 2b	−0.017***	—
	(0.005)	
8c. Equipment dummy 2c	−0.029***	—
	(0.005)	
9. Equipment dummy 3	−0.003	—
	(0.002)	
10. Equipment dummy 4	−0.005	—
	(0.003)	
11. Equipment dummy 5	0.022***	—
	(0.003)	
12. Age of dummy 5 equipment	−0.0013***	−0.0018***
	(0.0002)	(0.0007)
13. Equipment dummy 6	−0.004	—
	(0.006)	
14. Dummy for low computerization	−0.015***	—
	(0.003)	
15a. Maximum line speed	−0.00067***	—
	(0.00005)	
15b. (Maximum line speed)^2	8.1×10^{-7}***	—
	(7×10^{-8})	

TABLE A1—*Continued.*

Variable	OLS model with detailed controls	Fixed-effects model
16a. Maximum width	−0.0096***	—
	(0.0011)	
16b. (Maximum width)^2	0.00010***	—
	(0.00001)	
17. Dummy for type of end user	−0.039***	—
	(0.006)	
18. New equipment value during six-month installation	-3.1×10^{-6}***	-2.9×10^{-6}***
	(9.9×10^{-7})	(9.6×10^{-7})
19. Intercept	0.376***	—
	(0.075)	
R^2	0.409	0.073

* Significant at the 0.10 level.
** Significant at the 0.05 level.
*** Significant at the 0.01 level.

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