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The Effect of HRM Practices and R&D Investment on Worker Productivity

Fredrik Andersson, Clair Brown, Benjamin Campbell, Hyowook Chiang, and Yooki Park

1.1 Introduction

As the pace of technological change has quickened and global competition has shortened product life cycles, firms have had to rethink their technology investment strategies and their human resource management practices in order to remain competitive. The main contribution of this chapter is to examine the relationship between firm-level technological advance-

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ment (as proxied by research and development investment [R&D]) and firms' human resource management (HRM) practices for high-skill workers in a high-tech industry, and then examine how this relationship is connected to firm performance.

Although the relationship of technological change and labor market outcomes at the individual-worker level has been well-studied,[1] surprisingly little is known about what happens within the firm. Specifically, there is little empirical research on whether firms' technology choices are consistent with their human resource practices and whether there is a statistical relationship between technology, human resources, and performance at the firm level.

At the individual level, there is a long line of research observing the correlation of technical change and compensation for high-skill workers and examining the mechanisms underlying the relationship.[2] However, there is little large-scale work looking at the relationship of technology and worker outcomes within firms. In this project, we examine the worker/technology relationship within firms and focus on one specific industry where we can employ detailed industry controls.

Previous research has demonstrated that technology interacts with human resource practices through several channels. Technology may alter the development of and returns to human capital (Krueger 1993; Handel 1999; DiNardo and Pischke 1997; and Entorf and Kramarz 1998). Additionally, technology can interact with individual outcomes through changes in work design (Hunter and Lafkas 2003; Bresnahan, Brynjolfsson, and Hitt 2002; Zuboff 1988; Autor, Levy, and Murnane 2002; Brown et al. 1997; and Barley and Orr 1997) or changes in work organization (Cappelli 1996; Bresnahan, Brynjolfsson, and Hitt 2002; O'Shaughnessy, Levine, and Cappelli 2001; and Caroli and Van Reenen 2001).

We propose a mechanism connecting technology and HRM practices at the firm level that links the skill bias and the organization change approaches. We propose a make-versus-buy model of workforce skill adjustment. If technology and labor force skills are complements in a firm's production function, and if the HRM system impacts the cost of acquiring, developing, and retaining the portfolio of skills in a firm, then the firm's choice of HRM system affects its ability to adjust worker skill levels to maximize the value of their technological investments. In other words, if firms choose to augment the skill of their workforce to complement an investment in technology, they face the traditional make-versus-buy problem. Firms can structure their HRM practices to develop and retain the

1. See Brown and Campbell (2002) for a detailed review of the impact of technological change on the work and wages of individuals.

2. Seminal works in this area include Bound and Johnson (1992), Levy and Murnane (1992), Katz and Murphy (1992), Juhn, Murphy, and Pierce (1993), Berman, Bound, and Griliches (1994), and Allen (1997).

necessary skills in-house, or they can structure their HRM practices to attract and recruit workers with the necessary skills on the external market.

For the econometric portion of the chapter, we utilize data from the Longitudinal Employer-Household Dynamics (LEHD) program that covers all establishments and their employees in seven large states over the period 1992 to 2001. Our analysis and interpretation is informed by fieldwork through the Sloan Competitive Semiconductor Manufacturing Program. The fieldwork began in 1992 and involved detailed data collection and intensive interviews at over three dozen semiconductor manufacturing firms. The insights and understanding developed through these site visits are the basis of our examination of the HRM-technology-productivity relationship in manufacturing firms within the electronics industry.

The analysis capitalizes on the strengths of both detailed industry study and large-scale survey approaches to develop a framework for estimating the relationship between firm productivity, R&D, and HRM practices using near-universal data from the LEHD program. The detailed industry knowledge facilitates interpreting of the results and understanding the context in which the results are embedded. This combined method expands the "insider econometrics" approach to the industry level of analysis.

Industries exhibit wide variation in their market and organizational structures, which affects their rate of technological change, their degree of and response to global competition, and, in general, their reaction to environmental factors. Because industries differ in dimensions that are hard to measure using traditional large-scale survey responses, industry-specific knowledge gained through fieldwork is critical in understanding how to interpret estimated statistical relationships within and across industries (Brown, Haltiwanger, and Lane 2006). Fieldwork research allows us to study the trade-offs that managers make in developing and implementing new technology and HRM practices, and they help us understand the timing of these decisions. Although technology and HRM practices are related through the production process, we observe that technological changes can be implemented much faster and, therefore, more often than HRM practices can be changed. Firms' choice of HRM practices can be made more independently of the external market than the choice of a new technology, which is tied to a choice of customers and markets.

While it is important to understand the underlying structure of a firm to interpret results, detailed firm or industry studies cannot be used for generalizations across firms or industries or for estimating national impact because we do not know whether the specific firm experiences are representative (Sturgeon et al. 2006). In order to generalize from an industry study, we need estimations from a comprehensive survey across firms and workers in the industry that show the observed relationship across key variables, such as HRM practices, R&D expenditures, and productivity. Our approach is to combine comprehensive micro-data and detailed industry knowledge in a way that leverages each approach's strengths and increases the quality and usefulness of both types of data. For micro-data to be estimated and interpreted properly, research teams must have both a deep understanding of the industries involved and expertise in the use of micro-data.

Specifically, this study combines both micro-data and detailed industry knowledge to analyze the impact of R&D and HRM systems on firm performance within the electronics industry (Standard Industrial Classification [SIC] 35 and 36).[3] Although firms in the electronics industry have a high level of R&D investment relative to other industries, there is a large variance in investment between firms within the industry. Studying one industry simplifies the analysis of the relationship of R&D and HRM by focusing on firms that are fairly comparable in structure and face similar market trends and measurement issues.

We use workers' outcomes within establishments to construct a variety of measures of establishment-level HRM outcomes for high-education workers and then link these HRM measures to plant and firm characteristics. First, we document the firms' HRM systems. Implementation of HRM systems is more important than implementation of individual components because there are synergies and complementarities in HRM practices (Kandel and Lazear 1992; and Milgrom and Roberts 1995). We perform a cluster analysis of firms and HRM measures to identify and describe the most common HRM systems. Next, we employ principal components analysis to identify groups of correlated HRM measures. We then regress worker productivity on the principal HRM components interacted with R&D.

We find substantial variation in HRM practices for high-education workers across firms in this industry. Human resource management bundles appear to include both spot market and internal labor market outcomes. Consistent with Bauer and Bender's (2004) finding using comparable German data that technological advancement is correlated with worker churning for high-skilled workers, we find that for firms with high levels of R&D, HRM practices that provide multiple ports of entry, low turnover and performance incentives are positively related to worker productivity. For low R&D firms, HRM practices that offer multiple ports of entry and low wage variance for recent hires are positively related to productivity. Additionally, the results indicate strong clustering of HRM practices across firms, with high R&D firms much more likely to implement more market-oriented practices than low R&D firms in this high-tech industry. These findings are consistent with the implications of our make-versus-buy model of workforce skills, where firms with a high rate of technological change that buy

3. The LEHD program links universal and longitudinal records on employees' earnings and employment from states' Unemployment Insurance (UI) systems with detailed cross-sectional data from Census Bureau's Economic Censuses and Census/NSF R&D surveys.

new skills on the external market and selectively retain and reward experienced workers will demonstrate higher productivity than comparable firms with fewer ports of entry with similar earnings growth, which indicates more internal skill development. Also, firms with a low rate of technological change implement HRM systems that are consistent with providing training to workers rather than buying required skills, which may be more efficient in these firms with slower technological change.

The next section presents a framework for firms' R&D investment decisions and firms' HRM decisions and how these decisions are related to productivity. Then we describe the data set and our measurements for HRM practices, R&D investment, firm performance, and other firm characteristics. We present statistical results on firm performance, HRM, and R&D and discuss to what extent the results are consistent with our hypotheses. Finally, we conclude with a summary and a discussion of the implications of the research.

1.2 HRM Practices and Workforce Skill Adjustment Costs

Our analysis looks at HRM practices within firms and builds on the Internal Labor Market analysis embedded in the work of Prendergast (1996) and Doeringer and Piore (1971). In the empirical work, there is mixed evidence on measuring internal labor markets within firms. Using data from a single firm, Baker, Gibbs, and Holmstrom (1994) find that some aspects of the employment relationship are consistent with the theory of internal labor markets. Lazear and Oyer (2004) use matched data from the Swedish Employers Confederation from 1970 to 1990. They find that the strict model of internal labor markets does not seem to hold because external forces play a large role in firms' wage setting policies. Topel and Ward (1992) observe high mobility and earnings growth among young male workers that is more consistent with matching models and on-the-job search than internal labor markets. Because of the mixed evidence, we perform a cluster analysis of firms in our sample to examine the distribution of different sets of HRM practices and find a diverse set of HRM outcomes, even within a homogenous industry.

Given the diverse outcomes, we focus on developing an understanding of the underlying process that might explain the diversity. The basic concept of the framework is that HRM practices affect the cost structure of how firms adjust the skills of their workforce. If technology and worker skills are complementary, then the firm's HRM decisions and R&D decisions will be related.

Even in the high-tech electronics sector, the speed of technological change varies across firms in different product markets. For example, consider the semiconductor industry, which is one of the industries included in our sample. Within the semiconductor industry, graphic chips for video games typically have a generation life of approximately eighteen months and analogue chips typically have a generation life of five years. Memory chips and microprocessors typically have a generation life between two and three years. Generation life is critical in defining a firm's constraints in making technological investment, as product prices are above marginal costs early in the cycle before supply brings the prices down. Across the electronics industry more broadly, product life and speed of technological change have an even longer time horizon. For example, our sample also includes manufactures of "current-carrying wiring devices." In contrast to the semiconductor industry, the wire industry is marked by very long product life spans and low levels of innovation.

The firm's HRM system structures how labor inputs are bought and created over time. We assume the cost of labor inputs are determined by the following HRM practices:

- Screening and hiring
- Skill development (both learning by doing and formal training)
- Retention of experienced workers
- Adjustments in headcount by skill (quits and layoffs)

At any given point in time, these HRM practices determine the cost and skills of the firm's workforce. Here we focus only on high-education workers because they are the workers who develop and implement new technology.

If firms adopt a technological change that alters the optimal composition of their workforce, firms may choose to adjust the skills embedded in their workforce. Given the decision to adjust workforce skills, firms must make two major decisions in creating the optimal skill-experience composition in the workforce:

1. Decide whether to provide formal training in the new technology to their existing workers or to purchase these skills through new hires (we call this the make-buy decision)
2. Decide which experienced engineers (and other workers) they will retain (we call this the retention decision)

The firm will make the first decision based upon the relative costs, including both the payroll costs and the time-to-market costs, of making or buying the required skills for the new technology. Under the assumption that the cost of "making" the required skills is the worker adjustment cost of acquiring skills (training cost) and is proportional to the size of technological jumps over a given time, and that the cost of "buying" the required skills is the firm's adjustment costs in hiring new workers, which is invariant to the size of the technological jump, then for sufficiently large technological jumps, "buying" will be relatively less costly than "making" new skills.

The second decision will depend upon the costs of retention as well as the production function. Specifically, firms will structure incentive systems to retain the workers who are most valuable to the firm. For a new technology that requires new skills and restructures skill demand in the firm, the firm must decide which workers to retain. This decision depends on the portfolio of skills supplied in the firm compared to the portfolio of skills necessary for the new technology and the costs of obtaining the new portfolio, which include a comparison of the make decisions (primarily retraining costs) compared to buy decision (cost of new hires, layoffs, and worker morale). The costs to workers of retraining depend on their opportunity wage and the required effort associated with retraining, which depends on how much retraining is required. Workers with skill sets far behind the latest technology will face higher retraining costs but require lower incentives by the firm for retention, while workers who are better matches to the new technology will face lower retraining costs and the incentives required by the firm for retention are higher.

How does the firm's product life, and thus rate of R&D spending, affect how the HRM system operates? We assume that a new technology requires a mix of experience on the previous generation of technology and new skills that require formal education (or training). Firms in short product-life markets, and thus with high R&D spending, must have a mix of engineers with the new skills required for the new technology and engineers with experience on the last generation of technology, and we assume that experience and new skills are complements. Firms in long product-life markets, and thus with low R&D spending, rely more on engineers with experience because the engineers will focus on cutting costs, improving quality, and improving throughput over the life of the product.

If worker costs of retraining increases proportionally with size of technological change (as proxied by R&D), and firm hiring transaction costs are invariant to size of technological change, then R&D and flexible hiring practices will be positively related to worker productivity. In a competitive labor market, implementation of new technologies in an industry will impact the external market opportunities for engineers. To counteract turnover of key workers, who are the workers with skills more compatible with the new technology, firms will structure their HRM system to provide incentives (both in compensation and in job assignment) in order to retain workers who match well to the new technology and who face lower personal retraining costs. How long it is beneficial for the high R&D firm to retain and use their technical workers' skills will determine the incentive structure implicit in their pay system compared to opportunity market wages as well as their average tenure (and turnover rate).

HYPOTHESIS 1: *Firms with high R&D that choose an HRM system that allows hiring of workers with required skills and fosters retention of selected experienced workers will have higher worker productivity than those that create the required new skills strictly through retraining of workers or strictly through new hires.*

Firms with low R&D improve performance not through product market innovation, but through incremental improvement in the product and production process. Experience is valuable in making these improvements, and firms that provide incentives to retain workers will have higher productivity. Performance-based pay that is tied to improvements may also motivate workers to higher productivity, although this pay may be awarded to a team rather than an individual technical worker in order to encourage group activity and because evaluating individual contributions may be difficult.

HYPOTHESIS 2: *Firms with low R&D that choose an HRM system that fosters retention of experienced workers and allows some performance-based pay will have higher worker productivity than those that do not have a compensation structure that reduces quits and rewards improvements.*

In the next section, we discuss the data and measures we will use to examine the previous hypotheses linking HRM practices to worker productivity for firms on different technology paths.

1.3 Data Set and Measures

We use data from three sources in our analysis. We use longitudinal and near-universal individual data from the LEHD program to construct and characterize the human resource practices of firms; we add firm characteristics from the 1997 Economic Censuses (e.g., measures of revenue, material costs, total hours, capital stock, four-digit industry code) as well as from the 1991 to 1998 Census/National Science Foundation (NSF) R&D Surveys (firm-level R&D).

The LEHD data have been extensively described elsewhere (see Haltiwanger, Lane, and Spletzer 2000; Abowd, Haltiwanger, and Lane 2004),[4] but it is worth noting that these data have several advantages over household-based survey data. In particular, the earnings are quite accurately reported as there are financial penalties for misreporting. The data are current, and the data set is extremely large.

1.3.1 HRM Variables

In characterizing the human resource practices of a firm, we utilize the measures of earnings, earnings growth, accession rate, and separation rate for selected cohorts within each firm to create the following components of

4. The LEHD database consists of quarterly records of the employment and earnings of almost all individuals from the unemployment insurance systems of a number of U.S. states in the 1990s. The UI records have also been matched to internal administrative records at the Census Bureau that contain information on date of birth, place of birth, race, and sex for all workers.

firms' HRM systems for high-education (or professional) workers, who we know from our fieldwork are primarily technical workers:

- Accession rate: Ratio of the total number of new hires to the total number of workers in 1997.
- Ratio of mean initial wage to market initial wage: Average wage of new hires of an individual establishment divided by average wage of new hires of all establishments in electronics industry (SIC 35 and 36) in 1997.
- Standard deviation of initial earnings: Standard deviation of earnings of new hires in 1997.
- Separation rate for workers with two years experience: Proportion of workers who are no longer working for a certain establishment in 1997 among all workers who are hired in 1995 at the same establishment.
- Within-job wage growth for workers with two years experience: Wage growth between 1995 and 1997 of workers hired in 1995.
- Standard deviation of within-job wage growth for workers with two years experience: Standard deviation of wage growth between 1995 and 1997 of workers hired in 1995.
- Separation rate of workers with five years experience: Proportion of workers who are no longer working for a certain establishment in 1997 among all workers who are hired in 1992 at the same establishment.
- Within-job wage growth for workers with five years experience: Wage growth between 1992 and 1997 of workers hired in 1992.
- Standard deviation of within-job wage growth for workers with five years experience: Standard deviation of wage growth between 1992 and 1997 of workers hired in 1992.

One limitation of the data is that the current observed HRM practices in a firm reflect outcomes for workers who are both new to the firm and have been at the firm for any number of years. To capture the entire profile of workers and their wage growth, it is necessary to use the longitudinal variation in the data in order to construct the HRM measures. Currently the limited data on R&D expenditures allows us to examine only one cross section of the data, while the HRM measures capture longitudinal variation.

Another limitation for this study is that we lack direct measures of some important worker and job characteristics, especially education and occupation. We use imputed education values developed by the LEHD staff to distinguish high-education workers from other types of workers.[5]

5. While data on education for the individuals in our sample are not directly observed, LEHD staff has imputed education for every individual based on probabilistic links to external data. The statistical model takes advantage of the common observable characteristics in LEHD and Decennial data—most important earnings, industry, geography, gender, and

1.3.2 R&D Measure

The following variable represents firm-level technology practices: *R&D spending rate* is measured as the average total R&D costs per payroll over 1991–1998.

Because Census/NSF R&D surveys are conducted at the firm level, we assume that all establishments of the same firm equally benefit from their firm level R&D.

Research and development is just one component of firms' technology investment decisions, and as a result it is an imperfect proxy for investment in technology. However, R&D may be a good proxy for picking up firm's ability to learn and develop new knowledge (Cohen and Levinthal 1989). Also, because the relationship between R&D and new technology depends on the success of the investments and the length of period until implementation takes place, there may be an issue with the timing of investments and HRM choices. We partition the firms in our sample into two sets: firms with above-mean R&D investment and firms with below-mean investment.

1.3.3 Firm Performance Measure

To represent firm performance, we use following productivity measurement: *Labor productivity* is the log of real value added per total hours worked where the value added is the establishment-level revenue adjusted for inventory change net of materials input, and total hours worked include both production worker hours and nonproduction worker hours.

In the next section, we identify common HRM systems, the underlying HRM components that differentiate firms' HRM systems, and the relationship of these components to worker productivity.

1.4 Empirical Analysis

First, we perform a cluster analysis of firm HRM practices to identify the most common HRM systems for high-education workers. Next, we employ principal components analysis to identify groups of correlated HRM measures. We then implement a principal components regression to examine the statistical relationship of worker productivity with HRM practices for different technology paths.

1.4.1 HRM Cluster Descriptions

Firms implement HRM practices in bundles, and so we expect a high-level of correlation of adopted bundles across firms. We perform cluster

age—to impute education based on draws from the conditional distribution of educational categories in the 1990 Decennial Census. Details of the statistical model can be obtained from the authors.

analysis to identify the most common bundles of HRM practices implemented by firms and to group firms with similar practices. In order to maximize the degree of separations between the groups of firms, clusters of firms are based on canonical variables of HRM variables using Ward's minimum variance method.[6]

In table 1.1, we present the cluster results for the HRM variables for high-education workers (summary statistics of the first four clusters of HRM practices are reported, and the last group of firms represents the aggregation of multiple small clusters that are not disclosable according to Census Bureau confidentiality requirements).

Each cluster represents a prototype HRM system, which we indicate by name. We then discuss how we think the HRM system is operating within the firm based upon the components and our fieldwork observations.

- **Cluster 1 = Performance-Based Internal Labor Market (ILM):** Firms in Cluster 1 offer lower than average initial earnings and slow, but steady earnings growth, lower than average turnover and low earnings dispersion. These characteristics are consistent with hiring less-experienced workers and advancing them along well-defined pay scales. Entry of workers and their initial earnings reflect skill requirements, so average initial earnings of new hires are higher and have higher variance than in a bureaucratic ILM. After approximately two years, workers are selected (based upon performance) for faster career development, and members of a cohort compete for entry into these favored positions, which have higher earnings growth and lower separation rates. Those who do not receive skill development have lower earnings growth and higher separation rates.
- **Cluster 2 = Spot Market with Rewards:** Firms in Cluster 2 exhibit pay tied to the external labor market (both at entry and with experience) and above-average turnover. Firms can identify workers' talents and skills and hire and pay accordingly (matching is good). Firms can monitor worker performance and pay workers according to contribution. Initial earnings and earnings growth reflect market rates for skill

6. In Ward's minimum-variance method, the distance between two clusters is the analysis of variance (ANOVA) sum of squares between the two clusters added up over all the variables. At each generation, the within-cluster sum of squares is minimized over all partitions obtainable by merging two clusters from the previous generation (Ward 1963). The assumptions under which Ward's method joins clusters to maximize the likelihood at each level of the hierarchy are multivariate normal mixture, equal spherical covariance matrices, and equal sampling probabilities. Therefore, we first obtain approximate estimates of the pooled within-cluster covariance matrix of the HRM variables when the clusters are assumed to be multivariate normal with spherical covariance using the approximate covariance estimation for clustering developed by Art, Gnanadesikan, and Kettenring (1982). The Approximate Covariance Estimation for CLUStering (ACECLUS) procedure provides us with canonical versions of earnings (or person and firm effect), earnings growth, and worker churning that we use in the cluster analysis.

Table 1.1 **HRM practice clusters for high-education workers**

Variable	Cluster 1: Performance-based ILM	Cluster 2: Spot market with rewards	Cluster 3: Bureaucratic ILM	Cluster 4: Spot market	Residual firms	Sample
Accession rate	0.141	0.141	0.131	0.135	0.169	0.140
	(0.116)	(0.096)	(0.103)	(0.079)	(0.102)	(0.095)
Ratio of mean initial wage to market initial wage	0.807	1.027	0.539	1.153	1.437	0.830
	(0.382)	(0.214)	(0.265)	(0.180)	(0.222)	(0.350)
SD of initial earnings	6,108	10,024	2,754	13,672	21,430	7,419
	(10,210)	(1,029)	(987)	(1,188)	(594)	(5,939)
Separation rate at 2 years tenure	0.414	0.462	0.406	0.486	0.435	0.430
	(0.194)	(0.185)	(0.197)	(0.205)	(0.174)	(0.195)
Within job wage growth at 2 years tenure	0.052	0.066	0.071	0.056	0.067	0.060
	(0.071)	(0.061)	(0.061)	(0.076)	(0.067)	(0.068)
SD of within job wage growth at 2 years tenure	0.121	0.129	0.116	0.156	0.127	0.120
	(0.060)	(0.076)	(0.074)	(0.073)	(0.093)	(0.076)
Separation rate at 5 years tenure	0.425	0.452	0.403	0.446	0.531	0.430
	(0.176)	(0.172)	(0.197)	(0.163)	(0.171)	(0.177)
Within job wage growth at 5 years tenure	0.030	0.030	0.026	0.028	0.033	0.030
	(0.029)	(0.027)	(0.029)	(0.025)	(0.031)	(0.027)
SD of within job wage growth at 5 years tenure	0.054	0.060	0.053	0.055	0.062	0.060
	(0.030)	(0.019)	(0.030)	(0.022)	(0.025)	(0.024)
N	273	120	235	57	56	741

Notes: Table shows within-cluster means. Numbers in parentheses are standard deviations. HRM = human resource management. ILM = internal labor market. SD = standard deviation.

and talent, with large initial variance, and variance does not increase over tenure. Separation rate is higher than in ILMs.

- **Cluster 3 = Bureaucratic ILM:** Firms in Cluster 3 have very low initial earnings (with low variance), below-average earnings growth the first two years, and low turnover. Initial earnings of new hires are similar as most workers enter at the same level and have similar (and reliable) earnings growth. Firms experience low separation rates.
- **Cluster 4 = Spot Market:** Firms in cluster 4 offer high initial wages with large variance, below-average earnings growth (with large variance), and high turnover. Firms hire and pay workers as in spot market, but identification of worker's talents and effort at hire is imperfect and monitoring of worker performance is imperfect. Variance of initial earnings is higher than in spot markets with rewards. Early separation rate is higher than in spot market because the bad matches (both at hire and in rewards) end.

We find that firms are concentrated in clusters 1 and 3: 37 percent of all firms are in Cluster 1, 32 percent are in Cluster 3, 16 percent are in Cluster 2, and 8 percent are in Cluster 4; apparently the primary variables in differentiating systems are wage variation and initial earnings.

We classify firms as high or low R&D firms based on whether their R&D investment is above or below the mean and present their HRM cluster distributions in table 1.2. For low R&D firms, 82 percent are in Clusters 1 and 3 (ILMs), and 14 percent are in Clusters 2 and 4 (spot markets); for high R&D firms, 60 percent are in Clusters 1 and 3, and 31 percent in Cluster 2 and 4. This indicates that high R&D firms are more likely to implement spot-market-oriented HRM practices than low R&D firms although there are still many high R&D firms in the performance-based ILM cluster. Further, low R&D firms are more likely than high R&D firms to implement Bureaucratic ILMs, although there are many low R&D firms that implement performance-based ILM.

Table 1.2 **High-education HRM cluster sizes by firm R&D level**

	Low R&D firms		High R&D firms	
Cluster 1: Performance-based ILM	120	(16.2)	153	(20.6)
Cluster 2: Spot market with rewards	34	(4.6)	86	(11.6)
Cluster 3: Bureaucratic ILM	125	(16.9)	110	(14.8)
Cluster 4: Spot market	8	(1.1)	49	(6.6)
Residual firms	13	(1.8)	43	(5.8)

Notes: Numbers in parentheses are percentages. HRM = human resource management. ILM = internal labor market.

Table 1.3 Explained variance by HRM components

Component	Fraction of variance explained	Cumulative explained variance
1	0.255	0.255
2	0.172	0.428
3	0.135	0.562
4	0.108	0.671
5	0.091	0.761
6	0.077	0.838
7	0.061	0.900
8	0.056	0.956
9	0.044	1.000

Notes: Variance explained by relative weights of each factor's eigenvalues from a principal. HRM = human resource management.

1.4.2 HRM Principal Components Analysis

Because firms adopt discrete bundles of HRM variables, we anticipate a high degree of multicollinearity across the nine underlying HRM variables. In order to avoid overfitting our regression models, we implement a principal components regression framework.

First, we construct the principal components of the underlying HRM variables using eigenvectors of the correlation matrix as coefficients.[7] Each component is a linear combination of the underlying variables, and we retain the combinations that capture the most variance in the underlying data and then rotate the axes to facilitate interpretation of the components. In table 1.3, we present a summary of the variance explained by the nine HRM components. The values in the table represent a proportion of the eigenvalue from each principal component. We find that there is a lead HRM component with several secondary components of lesser importance. For the subsequent analysis, we focus on the first six components, which explain 84 percent of the variance for the set of HRM variables.

Table 1.4 reports the HRM component patterns for high-education workers.[8] The first component, which we label "ports of entry," corresponds to a high level of initial earnings relative to market and a high standard deviation in initial earnings. This is the lead component and indicates

7. These principal components are then ordered by variance, and the largest components are retained and then rotated to ease interpretation. Detailed descriptions of the technique are given in, for example, Sen and Srivastava (1990, 253–55) or Draper and Smith (1981, 327–32). While this technique has found use in some of the applied statistics literature, the technique has been shown to produce poor results in certain data sets (e.g., refer to Hadi and Ling [1998] for illustrations.)

8. The first six components from the principal components analysis were orthogonally transformed through a varimax rotation. Subject to a threshold test of .50 for significance, each human resources (HR) variable has a significant loading in exactly one component.

Table 1.4 HRM component patterns for high-education workers

Variable	Component 1: Ports of entry	Component 2: Turnover rate	Component 3: Wage growth	Component 4: Hiring rate	Component 5: Performance incentives	Component 6: Early matching
Accession rate	0.05	0.20	0.05	**0.94**	0.01	0.01
Ratio of mean initial wage to market initial wage	**0.89**	0.13	0.02	0.02	–0.01	0.05
SD of initial earnings	**0.82**	0.05	0.04	0.07	0.23	–0.02
Separation rate at 2 years tenure	0.01	**0.90**	–0.01	0.00	0.11	–0.08
Within-job wage growth at 2 years tenure	–0.07	0.02	**0.93**	–0.09	0.02	0.01
SD of within job wage growth at 2 years tenure	0.03	–0.07	0.01	0.01	0.06	**0.99**
Separation rate at 5 years tenure	0.22	**0.77**	–0.01	0.31	–0.08	0.00
Within-job wage growth at 5 years tenure	0.23	–0.06	**0.66**	0.35	0.28	0.00
SD of within-job wage growth at 5 years tenure	0.16	0.05	0.14	0.01	**0.95**	0.06

Notes: Component pattern matrix from the top six components of a principle components analysis with varimax rotation. Weights ≥ .50 are in boldface. SD = standard deviation. HRM = human resource management.

how many ports of entry are used by the firm, as opposed to hiring at an entry level and promoting from within. A high value on this component describes firms that hire workers at many different levels of experience and skill, which increases the level and variance in initial earnings. The second component, labeled "turnover rate," reflects a high separation rate after two and after five years of tenure. The third component, labeled "wage growth" reflects high levels of within-job wage growth after both two and five years of tenure. The fourth component, "hiring rate," reflects the overall hiring rate in 1997. The fifth component, "performance incentives," reflects a large variance in within-job earnings growth after five years tenure, which indicates that by this point the firm has selected certain workers for career development and advancement. The sixth component, "early matching," reflects a large variance in within-job earnings growth after two years tenure, which indicates that new hires are already selected for specific job tracks and career development.

In table 1.5, to check the correspondence between the components and the underlying variables, we present the means of each component for the HRM clusters from the previous section. The ILM systems (Clusters 1 and 3) have negative averages for ports of entry (with bureaucratic much lower than performance-based). Spot-market systems (Cluster 2 and 4) have positive means for turnover and for early matching. Overall, the component scores are consistent with our labeling of the clusters.

We further summarize the components by presenting component means by R&D level. Table 1.6 demonstrates that relative to low R&D firms, high R&D firms exhibit higher values for ports of entry, turnover, wage growth, hiring rate, early matching, and a lower rate for performance incentives. These differences are consistent with the suggestion that high R&D firms are more likely to implement more market-oriented HRM systems, and low R&D firms are more likely to implement HRM systems with more long-term performance incentives.

1.4.3 Worker Productivity Regressions

Next, we map the HRM variables for each firm to continuous variables corresponding to the components identified in the preceding and consider the impact of these HRM components on firm performance. Specifically, we regress productivity on the principal HRM components both with and without interaction with R&D spending. We measure firm performance as log worker productivity and control for log of physical capital (in order to capture capital intensity) and product market at the four-digit SIC (in order to capture product lifespan differences). We estimate two specifications: one specification with no R&D interactions and a second specification where R&D categories (high, low) are interacted with the HRM components. We employ principal components as regressors instead of the underlying HRM variables because of multicollinearity concerns and to

Table 1.5 **Component means for high education HRM clusters**

	Cluster 1: Performance-based ILM	Cluster 2: Spot market with rewards	Cluster 3: Bureaucratic ILM	Cluster 4: Spot market	Residual firms
Component 1: Ports of entry	–0.088	0.288	–0.606	0.570	1.206
Component 2: Turnover rate	–0.084	0.178	–0.103	0.249	0.216
Component 3: Wage growth	–0.081	0.036	0.059	–0.069	0.062
Component 4: Hiring rate	0.031	–0.143	–0.061	–0.265	0.056
Component 5: Performance incentives	–0.070	–0.016	0.014	–0.212	–0.261
Component 6: Early matching	–0.071	0.052	–0.131	0.381	0.058
N	273	120	235	57	56

Notes: See text for definition of clusters and factors. HRM = human resource management. ILM = internal labor market.

Table 1.6 High-education HRM component means by firm R&D level

	Low R&D firms	High R&D firms
Component 1: Ports of entry	–0.283	0.121
Component 2: Turnover rate	–0.023	0.016
Component 3: Wage growth	–0.100	0.058
Component 4: Hiring rate	–0.143	0.017
Component 5: Performance incentives	0.058	–0.141
Component 6: Early matching	–0.058	–0.004
N	300	441

Notes: See text for definition of components. HRM = human resource management.

address latent variable issues. As a robustness check, we also present results using a continuous measure of R&D in place of the dichotomous R&D measure.

We observe that several HRM components are related to worker productivity (see table 1.7). Specifically, firms with high levels of R&D investment are likely to benefit from HRM systems with multiple ports of entry, performance incentives, and lower turnover, while firms with low R&D are likely to benefit from HRM systems without early matching.

Firms with multiple ports of entry, which facilitate the hiring of workers with required skills, have higher labor productivity. This effect is more important (and significant) in the high R&D firms, which supports Hypothesis 1. Performance-based pay appears to be more important in high R&D firms than in low R&D firms. Firms with higher separation (turnover) rates appear to have lower firm performance, although this is significant only for high R&D firms. The effect of turnover rate on worker productivity appears to be significant only for high R&D firms, which does not support Hypothesis 2. Because these statistical relationships do not control for firms growing or shrinking, separation rates and hiring rates may reflect poor performing firms losing workers and high performing firms adding workers. Firms with early matching or sorting of workers appear to have lower worker productivity, although this is significant only for low R&D firms.

In tables 1.8 and 1.9, we examine the robustness of our results to changes in the construction of the R&D measure. Instead of the dichotomous measure used in the previous analysis, we examine if the results are robust to use of a continuous measure of R&D intensity. In table 1.8 we reestimate the model in table 1.7 where firm performance is a function of capital-labor ratio, continuous R&D, and HRM components. In the first specification, we have no R&D-HRM interactions; in the second specification, we interact HRM practices with the continuous R&D measure. In specification 1, we find very similar results to the model estimated with dichotomous

Table 1.7 High-education HRM components on firm performance

	Col. (1)	Col. (2)
Intercept	2.3187***	2.2247***
	(0.2491)	(0.2532)
ln(K/L)	0.3004***	0.3022***
	(0.0306)	(0.0306)
C1: Ports of entry	0.0837***	
	(0.0272)	
C1 × low R&D		0.0577*
		(0.0323)
C1 × high R&D		0.1397**
		(0.0500)
C2: Turnover rate	–0.0564**	
	(0.0264)	
C2 × low R&D		–0.0132
		(0.0413)
C2 × high R&D		–0.0829**
		(0.0346)
C3: Wage growth	0.0137	
	(0.0251)	
C3 × low R&D		0.0014
		(0.0352)
C3 × high R&D		0.0307
		(0.0359)
C4: Hiring rate	0.0389	
	(0.0262)	
C4 × low R&D		0.0842
		(0.0540)
C4 × high R&D		0.0326
		(0.0297)
C5: Performance incentives	0.0284	
	(0.0252)	
C5 × low R&D		0.0124
		(0.0406)
C5 × high R&D		0.0614*
		(0.0339)
C6: Early matching	–0.0146	
	(0.0246)	
C6 × low R&D		–0.0709**
		(0.0355)
C6 × high R&D		0.0450
		(0.0351)
R^2	0.66	0.66
N	760	760

Notes: Dependent variable is log worker productivity. Both specifications include controls for four-digit SIC. Standard errors in parentheses. HRM = human resource management.

*Denotes significance at the 10 percent level.

**Denotes significance at the 5 percent level.

***Denotes significance at the 1 percent level.

Table 1.8 **High-education HRM components and continuous R&D on firm performance**

	Col. (1)	Col. (2)
Intercept	2.3631***	2.2492***
	(0.2506)	(0.2580)
ln(K/L)	0.2979***	0.2966***
	(0.0306)	(0.0308)
R&D (continuous)	0.0332	0.0297
	(0.0219)	(0.0225)
C1	0.0794***	0.1664***
	(0.0273)	(0.076)
C1 × R&D		0.0291
		(0.0246)
C2	–0.0558***	–0.0543
	(0.0264)	(0.076)
C2 × R&D		–0.0004
		(0.0208)
C3	0.0111	0.0541
	(0.0252)	(0.057)
C3 × R&D		0.0193
		(0.0210)
C4	0.0358	0.0176
	(0.0262)	(0.044)
C4 × R&D		–0.0108
		(0.0199)
C5	0.0337	0.1021**
	(0.0254)	(0.052)
C5 × R&D		0.0277
		(0.0193)
C6	–0.0149	0.0478
	(0.0246)	(0.048)
C6 × R&D		0.0236
		(0.0141)
R^2	0.66	0.66
N	760	760

Note: See table 1.7 notes.
*Denotes significance at the 10 percent level.
**Denotes significance at the 5 percent level.
***Denotes significance at the 1 percent level.

R&D. However, when we examine the interactions in specification 2, we find differences between the continuous and dichotomous models. In the continuous R&D model, the turnover HRM practice (Component 2) is no longer significant, but the performance incentive practice (Component 5) is significant.

The differences in the interaction terms in the continuous and dichotomous models suggest that the relationship between R&D intensity and

Table 1.9 **High-education HRM components and R&D interactions on firm performance**

	Col. (1)
Intercept	2.2936***
	(0.2643)
ln(K/L)	0.3003***
	(0.0306)
R&D (continuous) × low	0.0357
	(0.0247)
R&D (continuous) × high	0.0448
	(0.0467)
C1 × low R&D	0.0552*
	(0.0324)
C1 × high R&D	0.1247**
	(0.0524)
C2 × low R&D	–0.0125
	(0.0413)
C2 × high R&D	–0.0823***
	(0.0346)
C3 × low R&D	–0.0025
	(0.0353)
C3 × high R&D	0.0293
	(0.0360)
C4 × low R&D	0.0882
	(0.0541)
C4 × high R&D	0.0254
	(0.0303)
C5 × low R&D	0.0206
	(0.0411)
C5 × high R&D	0.0611*
	(0.0343)
C6 × low R&D	–0.0716***
	(0.0356)
C6 × high R&D	0.0459
	(0.0351)
R^2	0.66
N	760

Note: See table 1.7 notes.

*Denotes significance at the 10 percent level.

**Denotes significance at the 5 percent level.

***Denotes significance at the 1 percent level.

HRM practices are not linear. In table 1.9, we estimate a model where we control for continuous R&D, but interact the HRM components with the dichotomous R&D indicator. We find highly similar results to the dichotomous interactions presented in table 1.7. Taken together, the two models suggest that the largest effect attributable to the interactions between R&D and HRM components occurs at the high-end of the R&D scale.

Overall, the regression results provide some preliminary evidence for Hypothesis 1 and mixed support for Hypothesis 2. The analysis suggests that high R&D firms benefit from HRM systems that offer multiple ports of entry, low turnover, and performance incentives, while low R&D firms benefit from HRM systems that offer multiple ports of entry and low wage variance for recent hires. The empirical results for high R&D firms are consistent with Hypothesis 1 because firms have higher productivity if they implement systems that allow hiring at many ports of entry and have tools to retain and retrain key workers. The empirical results on low R&D firms provide mixed support for Hypothesis 2. We do find that low turnover is correlated with firm performance; however, we did not hypothesize that ports of entry would play a substantial role in determining firm performance, and we do not find performance-based pay to have as large an impact as hypothesized. Although the flexibility in hiring at multiple ports of entry does not go with our strict rendition of ILM systems, this result is consistent with other empirical analyses that have found multiple ports of entry in ILMs (Baker, Gibbs, and Holmstrom 1994; Lazear and Oyer 2004).

1.5 Discussion

This chapter presents evidence of the relationship between firms' technology investment decisions, HRM practices, and productivity. We find that in the high-tech electronics industry, there is a positive correlation between performance and buying new skills (i.e., hiring at many ports of entry) for both high and low R&D firms, but the relationship is considerably stronger for high R&D firms. Interestingly, high R&D firms benefit from lower turnover and from having earnings that reward performance over a five-year period, which indicates that firms need to keep their technical workers, and the skills they have, for one project generation and into the next generation. Low R&D firms benefit from treating their workers comparably once they are hired, which indicates a positive correlation between performance and making new skills over time. In other words, high R&D firms appear to be more productive if they implement performance-based ILM systems, while low R&D firms appear to be more productive if they implement a modified bureaucratic ILM system that allows hiring at multiple ports of entry with comparable treatment once hired.

A key underlying assumption of our research method is that we can infer HRM practices statistically from administrative data. Although it would be interesting to compare our inferred HRM practices to company descriptions or employee perceptions of HRM systems in place, the data do not allow this. Fieldwork observations indicate that actual practices and company-described HRM policies are often divergent (Pfeffer and Sutton 1999). Our inferred practices are consistent with our previous research on the semiconductor industry, where we directly observed HRM practices through field work. Using extensive data collected from in-depth site visits, Brown and Campbell (2001) demonstrate that more-advanced semiconductor fabrication plants pay higher initial wages and have shorter career paths than less-advanced plants. These results from the field work data are similar to the results in this administrative data-based project. The similarity provides evidence that inferring HRM practices from administrative data is a sound practice.

A strength of this research is the richness of the data set utilized combined with interpretation through the lens of detailed industry knowledge. There is very little research that ties observed firm-level HRM systems to performance outcomes: the LEHD data allows us to analyze HRM systems and outcomes within firms for a large sample of firms, and the detailed industry knowledge allows us to understand the important issues and the context of the results. While the LEHD data provide ample sample sizes and longitudinal variation, the lack of direct measures of workers' skills or occupation and of technological change constrains the statistical estimation and limits our interpretation of the results.

Although these results must be interpreted with care, they have potential implications for understanding the mechanisms that tie together technological change and workers' outcomes. Because technological change impacts workers at the plant level, knowledge of how HRM systems interact with technological investment to drive productivity at the plant level will inform our understanding of how labor markets work in technologically dynamic industries.

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