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

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ABSTRACT

Using data on a large sample of electronics firms in seven large states from a newly developed employer-employee matched database (Longitudinal Employer Household Dynamics, LEHD), we examine the impact of human resource management (HRM) practices and technology on worker productivity. Motivated by extensive site visit research in the semiconductor industry in which we observe the interaction of HRM practices, technology and product markets, we use linked employer-employee data to test the generalizability of our case study observations. Specifically, we examine the relationship between product markets and HRM practices. Empirically, we identify HRM clusters for firms based on firm-level observations of nine measures of HRM outcomes. Next, we use principal components analysis to examine the relationships between the HRM measures. Then we use these principal components and their interactions with R&D investment as explanatory variables in a worker productivity regression. We find that there are large differences on the impact of human resource practices on labor productivity across levels of technological investment. Our preliminary results indicate that firms with high levels of R&D investment and HRM systems with multiple ports of entry, performance incentives, and lower turnover have higher worker productivity than comparable high-R&D firms without these HRM practices. Similarly, firms with low R&D that implement HRM systems with performance incentives have higher productivity than low R&D firms without performance incentives. These results suggest that high R&D firms are more likely to buy new skills compared to low R&D firms, and yet these high R&D firms suffer if they lose too many experienced workers. These findings are consistent with the implications of our "make versus buy" model of workforce skill adjustment as a response to technological change.

1. Introduction

As the pace of technological change has quickened, and as 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. This paper examines the relationship between firm-level research and development investment (R&D) and firms' human resource management (HRM) practices in a high-tech industry.

In a series of site visits of leading semiconductor fabrication plants as part of the Sloan UC-Berkeley Competitive Semiconductor Manufacturing Program we observed that firms often tailored their HRM system to their product market. Anecdotally, firms in markets where products obsolesced quickly appear to be more likely to implement spot market-based HRM practices while firms in markets with long product lives are more likely to implement internal labor market-based HRM systems. Using linked employer-employee data from the US Census Bureau we can test whether our anecdotal evidence generalizes across the universe of semiconductor and electronics firms.

There are several channels through which firm R&D and HRM decisions may be related. If technology and labor force skills are complements in firms' production functions, and if HRM systems impact the cost of acquiring, developing, and retaining the portfolio of skills in a firm, then firms' choice of HRM system affects their ability to adjust worker skill levels to maximize the value of their technological investments. For example, if firms need to augment the skill of their workforce to complement an investment in technology, they face a traditional "make versus buy" problem. Firms can structure their HRM system to develop the necessary skills in-house or they can structure their HRM to attract workers with the necessary skills on the external market. Also, workers gain skills directly from learning-by-doing in their R&D activities, which triggers the firm to enact HRM policies that retain the increasingly productive knowledge workers. Additionally, firms' product strategies directly affect both their R&D choices and their HRM choice (Lazear (1998) and Baron and Kreps (1999)).

Although the relationship of technological change, compensation and tenure at the individual level has been well-studied, surprisingly little is known about the relationship between technological change and *firms'* HRM decisions. Previous research on this topic has been either case study oriented or has utilized data from broad establishment-level surveys. Motivated and informed by our direct observation on semiconductor firms, this project connects these micro and macro approaches by using data that allows us to capitalize on the strengths of each type of research. Using data from the Longitudinal Employer-Household Dynamics (LEHD) Program, we are able to examine the HRM practices and firm-level characteristics for many firms in seven states, which allow us to build on the breadth of the establishment-level survey research. Additionally, we can track the outcomes of the universe of workers within each establishment. We use this broad sample and detailed measures to examine the HRM-productivity link in the electronics industry, where technological investment is a critical strategic variable.

Using data from the LEHD program for seven large states over the period 1992-1997 we estimate the relationship between the interaction of technological investment and HRM practices and firm performance. Specifically, we look at the impact of R&D and HRM systems on firm performance within the electronics industry (SIC 35 and 36). 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. This variance can be observed in the length of product life cycles: from twelve months for fast-evolving consumer-based products such as graphics chips, to five years or more for slowly-evolving analog products. 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 problems.

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 a variety of Census and BLS data collection programs on households and employers. We use the UI records on workers' outcomes within establishments to construct a variety of measures of establishment-level HRM outcomes for high-educated and low-educated workers. We then link these HRM measures with plant and firm characteristics collected from the Census Bureau's Economic Censuses and Census/NSF R&D surveys.

We employ principal components analysis to identify groups of correlated HRM measures. We then regress worker productivity on the principal HRM components interacted with clockspeed. While these results illustrate the relationships between performance, HRM practices and R&D, they do not describe the HRM practices actually implemented by establishments. Implementation of HRM systems is more important than individual characteristics 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.

We find that there are large differences in the impact of human resource practices on labor productivity across levels of technological investment. For firms with high levels of R&D, HRM practices for high-educated workers associated with having multiple ports of entry, a high hiring rate[1], and awarding performance incentives are positively related to worker productivity. High R&D firms implementing HRM systems for low-educated workers with performance incentives, high hiring rate, and low turnover have higher productivity. For low R&D firms, high-educated HRM practices that demonstrate performance incentives are positively related to productivity, while for low-educated workers, firms offering job ladders with varying amounts of career development so that workers' earnings streams diverge over time demonstrate higher productivity. These findings are consistent with the implications of a "make versus buy" model of workforce skills where the costs of training workers to acquire new skills associated with

[1] The measures of hiring rate and turnover are directly tied to firm employment growth so these measures may not capture HRM system outcomes as much as they capture firm growth. In the next iteration of this paper, we will explore this distinction.

a technological innovation are proportional to the size of the innovation, while the adjustment costs of hiring workers with the necessary skills are invariant to the size of the innovation. Specifically, firms with a high rate of technological change that buy new skills on the external market and selectively retain experienced workers will demonstrate higher productivity than comparable firms with a less flexible HRM system. Also, firms with a low rate of technological change that demonstrate performance incentives and selective retention will have higher productivity than comparable firms that do not demonstrate these HRM outcomes.

The next section briefly describes previous research on firm's earnings structure and performance with special focus on studies that explore the role of technology or that use matched employer-employee data. Then we describe a conceptual framework of the interrelationship of firms' R&D investment decisions and firms' HRM decisions on productivity. Next we describe the data set and our measurements for HRM practices, R&D investment, firm performance and other firm characteristics. Then we present some preliminary statistical results on firm performance, HRM, and R&D. Finally, we discuss our next steps.

2. Technology, HRM Practices, and Productivity

Using linked employer-employee data to analyzing the impact of HRM practices and technological investments on firm performance builds directly on the long line of literature exploring the link between HRM practices and firm performance. We also draw upon key aspects of the skill-biased technical change literature, the internal labor market literature, and the firm clockspeed literature.

Previous analysis of the relationship between HRM and performance focused on detailed understanding and knowledge of a specific firm (Ichniowski, 1992; and Berg et al, 1996), in-depth research of an industry (Kelley, 1996; Ichniowski, Shaw, and Prennushi, 1997; Brown et al., 1999; and Brown and Campbell, 2001), or analysis of representative surveys (Huselid, 1995; Huselid and Becker, 1996; and Black and Lynch, 2001). The survey-driven analysis is marked by using large data sets on employers to measure both firm performance and HRM practices. Our approach is to use novel data from the LEHD program to build on the previous research of the HRM-firm performance link.

Building on the work of Davis and Haltiwanger (1991), Doms, Dunne, and Troske (1997), and Jensen and Troske (1997) who use the Longitudinal Research Database (LRD) to study changes in wage distributions at the plant level, Black and Lynch (2001) use the LRD linked with a nationally representative survey of work practices to estimate an augmented Cobb-Douglass production function. The authors use both within and Generalized Method of Moments estimators and find that how HRM practices are implemented is more important than which HRM practices are implemented. We extend on their analysis by focusing on one specific industry where we can employ more detailed industry controls, and instead of using self-reported measures of HRM practices we focus on HRM outcomes measured for all workers in each establishment.

Our analysis of the relationship of technology and HRM practices complements the extensive body of literature on the relationship of technological change and workers' wages. The existing literature consists of two components. One line of literature examines the relationship between technology and wages, while the other examines the direct impact of technology on work organization. There has been extensive research documenting the impact of technology on wages and work at the individual level. However, currently little is known about how firms' R&D decisions affect firms' compensation policies. Below we track the evolution of the two arcs of the technical change literature to motivate our firm-driven approach.

The foundation of the line of literature linking technological change to wages uses Current Population Survey (CPS) data to document and analyze compensation patterns in the United States. Bound and Johnson (1992), Levy and Murnane (1992), Katz and Murphy (1992), and Juhn, Murphy and Pierce (1993) all use CPS data and observe shifts in wage levels that are consistent with the hypothesized effects of skill-biased technological change. Additionally, Juhn, Murphy, and Pierce (1993) demonstrate that within-group wage variation comprises a larger portion of the increase in inequality than between-group variation. Berman, Bound, and Griliches (1994), and Allen (1997) find similar results using industry-level data.

One channel through which the observed shifts in wage structures can be explained is that technical change augments workers' skills as they learn to use new technologies and new processes. Krueger (1993), Handel (1998), DiNardo and Pischke (1997), and Entorf and Kramarz (1997) analyze the returns to specific technologies on workers' wages and find a significant impact. However, DiNardo and Pischke also demonstrate the magnitude of the computer-use premium is similar to the pencil-use premium, while Entorf and Kramarz show that workers who begin to use a new technology are already more skilled and more highly paid than their peers.

Combining firm-level technology data and individual-level labor market data allows an analysis of firms' technology and HRM decisions. Most of the above studies show that wage structures are changing between plants and within industries and indicate that technology plays a role in the evolution of wage structures. They connect technology to changing skill demand and then to changes in wages. However, these firm-level decisions occur simultaneously.

Another channel that technology can impact worker and firm outcomes is through work organization. Hunter and Lafkas (1998) and Bresnahan et al, (2002) demonstrate that the impact of technology on work depends upon the HR system in which it was imbedded. Zuboff (1988) shows how digital technology has dramatically changed work by automating routine tasks and allowing some workers to perform new kinds of work in both manufacturing and service companies. Levy and Murnane (1996), Autor, Levy, and Murnane (1999), Barley and Orr (1997) and Brown et al (1997) argue that job tasks include routine or rule-based problem-solving operations, which can easily be done by a computer, and exceptions or model-based problem-solving, which cannot be done economically by a computer. The use of computers results in these exceptions shaping the demand for labor both in terms of quantity and skills.

Technological change is also related to organizational change within a firm which may impact both workers' outcomes and firm performance. Technology may be correlated with decentralized decision-making (Cappelli, 1996; and Bresnahan, et al, 2002), changes in bargaining power (O'Shaughnessy, Levine, and Cappelli, 1999; and Caroli and Van Reenen, 1998).

Our analysis looks at HRM practices within firms and builds on the work of Prendergast (1996) and Doeringer and Piore (1971). Pendergast provides an overview of the empirical literature on how compensation practices influence productivity and earnings. He concludes that theoretical and data limitations make it difficult to produce testable hypotheses that would distinguish the competing theories of incentives and outcomes. 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. The firm has a clear hierarchy of jobs and promotions and a strong relationship between jobs and pay that leads to a tendency toward long careers. However, they find little evidence of "ports of entry" into the firm, since the firm does a fair amount of outside hiring even at higher levels. Lazear and Oyer (2003) 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. External forces play a large role in firms' wage setting policies. Topel and Ward (1992) produce results that question the standard notion of human capital investment and lifecycle earnings growth. Using a longitudinal panel of earnings records from the social security program, they 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. Once good matches are found, these workers eventually settle down into jobs that are more stable.

In addition to the effects of human capital acquisition and internal labor markets on earnings profiles, industry characteristics such as rate of technological change, or "clockspeed" should affect the firm's human resource practices. Influenced by the evolution of fruit flies, Fine (1998) analyzes how each industry evolves at different rates, or "clockspeeds," depending "on its product clockspeed, process clockspeed, and organization clockspeed." (Fine, p. 6). Previous studies have looked at the impact of clockspeed on R&D (Mendelson and Pillai, 1998) and organizational structures (Mendelson, 2000). In a fast-clockspeed industry, the product life cycle is very short; technological change for both product and process development is rapid and technology depreciates quickly. Organizational forms are turbulent, as companies enter and leave, merge with or acquire each other, and spin-off off new companies. Although Fine's main thesis is that design of the supply chain provides the firm's ultimate core competency for maintaining advantage, his discussion of firm organization indicates that company systems, including HRM practices, affect performance and outcomes. In his model, firms in industries with fast clockspeed must continually innovate in order to stay competitive and must adopt different strategies to remain competitive than firms in slow-clockspeed industries that evolve more slowly.

In the next section we draw upon these many streams of literature by sketching a model that connects a firm's R&D decision, HRM practices and firm performance. The underlying concept of the model is that HRM practices affect the cost structure of how firms adjust the skills of their workforce. If technological investment is complementary to adjusting the workforce skills, firms HRM decisions and R&D decision will be related and will impact firm performance.

3. Conceptual Framework of HRM System, Technology Investment, and Firm Performance

Here we develop the conceptual framework that structures and informs our empirical analysis, which focuses on the relationship between firm performance and the firm's human resource management (HRM) system, given its product market and the corresponding technology. Our framework depends upon several critical assumptions, which lead to our two sets of hypotheses.

We assume that firm performance, especially worker productivity, will be impacted by the choice of HRM for given a technology, where technology is characterized by its length of product life (often called fast or slow clockspeed) or rate of change over time. Further, we assume that firm assets have a high degree of technology specificity across generations so firms are locked in to a technology path. Since we do not have direct data on the length of product life, we assume that product markets with short product life require relatively large R&D investments compared to product markets with long product life.

Since we are analyzing only the high-tech electronics sector, the idea of different lengths of product life, or speed of technological change over time, may not be obvious. Let us look at examples from the semiconductor industry, which is one of the industries included in our sample, where 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 a return on investment, since 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 has 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.

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). We further assume that the required formal education is much more time intensive for engineers than for direct labor. 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 a workforce with experience since workers focus on cutting costs, improving quality, and improving throughput over the life of the product. Firms must make two major decisions in creating the optimal skill-experience composition in the workforce, and especially in the engineering 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. 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. 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. Therefore, depending on firms' underlying cost structures, 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 lower and the incentives required by the firm for retention are higher.

What are the possible HRM systems that firms may set up as a result of the make-buy and retention decisions? Following the literature (above), we define four HRM systems according to their reliance on internal rules (called internal labor markets or ILMs) or on the external labor market (called spot markets), with variation between the two extremes based on assumptions about the firm's ability to identify worker talent and monitor performance. We characterize the HRM systems according to initial earnings (relative to market initial earnings), variance of earnings at points in time, wage growth over time, and separation rates, with these variable defined for specific cohorts of workers (i.e., same year of entry into firm).

Bureaucratic ILM: Initial earnings of new hires are similar (low variance) since most workers enter at same level and have similar (and reliable) earnings growth. Firm experiences a low separation rate.

Performance-based ILM: Entry of workers and their initial earnings reflect skill requirements, so average initial earnings of new hires are higher with higher variance than for 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.

Spot Market: Firm can identify workers' talents and skills, and hire and pay accordingly (matching is good). Firm can monitor worker performance and pay worker according to contribution. Initial earnings and earnings growth reflect market rates for skill and talent, with large initial variance, and variance does not increase over tenure. Separation rate is higher than in ILMs.

Spot Market with Rewards: Firm hires and pays 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 lower than in spot market. Firm must include performance rewards and tournament or wage-efficiency type incentives, thus variance of earnings increases over tenure. Earnings growth is higher than in spot market. Separation rate is higher than in spot market since the bad matches (both at hire and in rewards) end.

Our assumptions about skill and experience requirements based upon the firm's product market and R&D spending lead us to the following hypotheses about the relationship between choice of HRM and worker productivity:

Hypothesis 1A: *Firms with high R&D that choose an HRM system that allows hiring of workers with required skills will have higher worker productivity than those that create the required new skills through retraining of workers.*

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.

Hypothesis 1B: *Firms with high R&D that choose an HRM system that fosters retention of selected experienced workers will have higher worker productivity than those that do not have incentive/reward programs to retain selected workers.*

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.

We combine these two hypotheses into the following interacted hypothesis:

Hypothesis 1C: *Firms with high R&D that choose a "Spot Market with Rewards" HRM system will have higher worker productivity than those that choose other HRM systems.*

The "Spot Market with Rewards" system provides high R&D firm with required new skills through new hires and flexibility to adjust the workforce. Firms with high R&D that choose a "Bureaucratic ILM" HRM system will have lower worker productivity than firms that choose other HRM systems, since this system requires firms to retrain workers and does not provide adequate flexibility to adjust the workforce.

Hypothesis 2A: *Firms with low R&D that choose an HRM system that allows some performance-based pay will have higher worker productivity.*

Firms with low R&D improve performance not through product market innovation, but through incremental improvement in the product and production process. Performance-based pay that is tied to improvements will motivate workers to higher productivity.

Hypothesis 2B: *Firms with low R&D that choose an HRM system that fosters retention of experienced workers will have higher worker productivity than those that do not have an incentive structure that reduces quits.*

The rationale underlying this hypothesis is similar to Hypothesis 1B. In competitive labor markets, firms that do not provide incentives to retain key workers will lose their best workers to competitors who do provide incentives.

Again, we can combine these two hypotheses into the following interacted hypothesis:

Hypothesis 2C: *Firms with low R&D that choose a "Performance-based ILM" HRM system will have higher worker productivity than firms that choose other HRM systems.*

The "Performance-based ILM" system provides workers with incentives to reduce costs and improve quality on a product over time, and creates an experienced workforce. Firms with low R&D that choose a "Spot Market" HRM system will have lower worker productivity than firms that choose other HRM systems, since this does not creates incentives for retention, and the loss of experienced workers will reduce the firm's ability to reduce costs and improve quality.

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 technological paths.

4 Data Set and Measures

As discussed in the framework above, we are investigating the relationship between firms' productivity, their observed human resource management practices and their level of technology investment. To accomplish this goal we use data from three sources. First, to characterize the human resource practices of firms and industries, we use data from the U.S. Census Bureau's Longitudinal Employer Household Dynamics Program (LEHD). We then integrate LEHD data with information from the 1997 Economic Censuses, which provide a set of measures to characterize the technological decisions across firms. Finally, we integrate information from Census/NSF R&D Surveys in 1991-98 to get data on R&D.

4.1. The Analytical Dataset

LEHD database consists of quarterly records of the employment and earnings of almost all individuals from the unemployment insurance systems of a number of US states in the 1990s.[2] These data have been extensively described elsewhere (see Haltiwanger, Lane, and Spletzer 2000; Abowd, Haltiwanger, and Lane 2004), but it is worth noting that these data have several advantages over household-based survey data. In particular, the earnings are quite accurately reported, since there are financial penalties

[2] Given the sensitive nature of the dataset, it is worth discussing the confidentiality protection in some detail. All data that are brought in to the LEHD system have been anonymized in the sense that standard identifiers and names are stripped off and replaced by a unique "Protected Identification Key" or PIK. Only Census Bureau employees or individuals who have Special Sworn Status are permitted to work with the data, and they have not only been subject to an FBI check but also are subject to a $250,000 fine and/or five years in jail if the identity of an individual or business is disclosed. All projects have to be reviewed by the Census Bureau and other data custodians, and any tables or regression results that are released are subject to full disclosure review.

for misreporting. The data are current, and the dataset is extremely large. The Unemployment Insurance 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.

In this study, we use data from LEHD for seven states, including some of the largest in the U.S., over the period 1992-2001. 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. From the 1997 Economic Census, we obtain measures of revenue, material costs, total hours, capital stock, industry code, as well as establishment identifiers for almost the universe of establishments. The crosswalk between these files is based on 1987 SIC code for industry level sample and a common business-level identifier for establishment level sample.

We use an establishment-level dataset in the Electronics Industry (SIC 35 and 36). We choose to focus on the electronics industry for this study because although the industry as a whole has experienced rapid technological change, sub industry groups (4-digit SIC) and individual firms vary in their pace of technological change.

4.2. HRM Variables

In order to classify the HRM practices for each establishment in every quarter, we examine the following variables that make up components of firms' HRM systems for a given occupation group such as engineers, direct labor, or administrative support:

- 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 2 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 2 years experience: Wage growth between 1995 and 1997 of workers hired in 1995.
- Standard deviation of earnings for workers with 2 years experience: Standard deviation of 1997 earnings of workers hired in 1995.
- Separation rate of workers with 5 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 5 years experience: Wage growth between 1992 and 1997 of workers hired in 1992.

- Standard deviation of earnings for workers with 5 years experience: Standard deviation of 1997 earnings of workers hired in 1995.

One limitation for this study is that we lack direct measures of some important worker and job characteristics, especially education and occupation. In order to analyze the relationship only on R&D and HRM for knowledge workers, we use imputed education values developed by the LEHD staff to distinguish knowledge workers from other types of workers. In this paper we empirically examine not only all workers, but also workers imputed to have college degrees or more.

4.3. R&D Measure

In the empirical exercises, we examine the following variables to represent firm-level technology practices:

- R&D spending rate: measured as the average total R&D costs per payroll over 1991-1998.

Since 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.

R&D is just one component of firms' technology investment decisions, and as a result it is an imperfect proxy for investment in technology. Also, since 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.

4.4. Firm Performance Measure

- Labor productivity: 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 non-production worker hours.

In the next section, we use the LEHD variables on HRM outcomes, R&D, and worker productivity to identify common HRM systems, the underlying HRM components that differentiate firms' HRM systems, and the impact of these components on worker productivity.

5. Empirical Analysis

First, we perform a cluster analysis of firm HRM practices to identify the most common HRM systems. Next, we employ principal components analysis to identify groups of correlated HRM measures. We then regress worker productivity over firm HRM components with R&D interaction to examine the statistical relationship of worker productivity with HRM practices for different technology paths.

5.1 HRM Cluster Descriptions

We perform cluster 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. In Ward's minimum-variance method, the distance between two clusters is the 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 et al (1982), (ACECLUS). The 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.

Under the assumption that firms implement different HRM systems for high-skilled and low-skilled workers, we examine the HRM variables for high-education workers and for low-educated workers separately. Summary statistics of the first four clusters of HRM practices for high-educated workers are reported in Table 1. Firms in cluster 1 offer low initial earnings, steady earnings growth, low turnover and low earnings dispersion, which are consistent with hiring less experienced workers and advancing them along well-defined pay scale, as in a bureaucratic ILM system. Firms in Cluster 2 offer high initial wages with large variance, average earnings growth for the labor market, earnings dispersion that falls during first two years, high early turnover and low late turnover, which are consistent with good screening and matching at entry, as in a spot market,. Cluster 3 has average initial earnings, high earnings growth with high earnings dispersion, high early turnover and high late turnover, which is consistent with pay tied to the external labor market at entry and then a tournament model to select workers for promotion or a wage-efficiency type incentives mechanism, as in a spot market with rewards. Firms in cluster 4 have above-average initial earnings with moderate dispersion, below-average earnings growth, high earnings dispersion after two years, low early turnover and high late turnover, which is consistent with an ILM with multiple ports of entry and selection of workers for career development with turnover of workers not selected (a performance-based ILM). The last group of firms represents the aggregation of multiple small clusters that are not disclosable according to Census Bureau confidentiality requirements. Firms are concentrated in cluster 1: 58% of all firms are in cluster 1, 20% are in cluster 2, 16% are in cluster 3, and 4% are in cluster 4 and it appears that the primary variables in differentiating systems is wage variation and initial earnings.

In Table 2, we classify firms as high- or low-R&D firms based on whether their R&D investment is above or below the mean, and then present the cluster sizes of HRM practices for high-educated workers at different levels of R&D. First, the R&D distribution is quite skew with 59% of all firms above the mean. Within each R&D bracket, we observe different distributions of firms across the HRM clusters. Low R&D firms are over-represented in the “Bureaucratic ILM cluster” (i.e. 65% are in cluster 1), high R&D firms are over-represented in the “Bureaucratic ILM cluster” and “Spot-market cluster” (i.e., 52% are in cluster 1 and 25% are in cluster 2). Altogether, the low R&D firms are more likely than the high R&D firms to have ILM-style HRM; clusters 1 and 4 represent 70% of low R&D firms and 55% of high R&D firms. Spot market-style HRM is more likely to be found at high R&D firms (41% are in clusters 2 and 3) than at low R&D firms (29%). The high R&D sample also has more firms in the residual category (4% relative to 2% for low R&D firms).

We perform the same cluster analysis on low educated worker outcomes (see Table 3). For low-educated workers, the first cluster dominates, representing 82% of all firms. Cluster 1 represents a bureaucratic ILM with low initial earnings and low variance, steady earnings growth, and low earnings dispersion. Cluster 2 represents a spot market with matching at entry with above average earnings that reflects workers’ skill and experience, average earnings growth. This cluster comprises 16% of firms in the industry. The third cluster represents a performance-based ILM where firms hire experienced and skilled workers and so have high initial earnings, have low turnover for first two years, have high earnings growth after two years with large wage dispersion as selected workers have career development and advancement. Cluster 3 represents less than 1% of all firms. Cluster 4 represents a spot market with rewards, with high initial earnings that reflects workers’ skill and experience, high earnings growth, a very high separation rate as workers who do not get advanced are separated, and large variance in earnings, especially at the end of five years. This cluster makes up about 1.5% of the sample. As with the high-educated clusters, the last group represents several small clusters aggregated for disclosure purposes. Also, we are unable to present cluster sizes by R&D levels for HRM systems of low-educated workers because several of the cells are too small to disclose.

Firms are more dispersed in their choice of HRM systems for high educated workers than for low educated workers. For low educated workers, 82% of firms implement a bureaucratic ILM system; for high educated workers, 58% of firms implement a bureaucratic ILM system. The next most common HRM system implemented in this high-tech industry is a spot market, which matches workers at entry. For low educated workers, 16% of firms had a spot market HRM system; for high educated workers, 20% of firms had a spot market HRM system.

5.2 HRM Principal Components Analysis

In this section we examine our nine underlying HRM measures for each education group to identify correlations between the variables in firms' HRM implementations. Principal components analysis constructs the correlation matrix for our underlying variables and then constructs components that are linear combinations of the underlying variables using eigenvectors of the correlation matrix as coefficients. These principal components are then ordered by variance and the largest components are retained, and then rotated to ease interpretation. In other words, 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. We will focus on two sets of data: HRM outcomes for high-educated workers and HRM outcomes for low-educated workers.

In Table 4, we present a summary of the variance explained by each set of components, as a proportion of the eigenvalue from each corresponding principal component. We present results for the set of nine HRM measures for each education group. We find that for both education groups, there is a lead HRM component with several secondary components of equal importance. In both cases, the first component has a relatively large amount of explanatory power; the next several components are relatively equal in magnitude. For the subsequent analysis we focus on six components, which explain 85% of the variance for the set of high educated worker variables and 91% of the variance for the set of low educated worker variables.

The first six components from the principal components analysis were orthogonally transformed through a varimax rotation. Table 5 reports the rotated component pattern matrix for high educated workers. The first component, which we label as "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 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 of high-educated workers after two and five years of tenure. The third component, labeled "performance incentives," corresponds to a high level of within-job wage growth and large earnings variance at the fifth year of tenure, which indicates that by this point the firm has selected certain workers for career development and advancement. The fourth component, "wage growth" reflects high levels of within-job wage growth at both the second and fifth years of tenure. The fifth component, "hiring rate" simply reflects the overall hiring rate in 1997. The sixth component, "early sorting" reflects the standard deviation of wages in the second year of tenure. Subject to a threshold test of .50 for significance, each HR variable has a significant loading in at least one component. The within-job wage growth at five years tenure is the only HR variable that has a split loading over components 3 and 4.

In Table 6, 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. Cluster 1, the bureaucratic ILM system, has low average values across all the components. The cluster has notably low values for the ports of entry, performance incentives, and early sorting components which captures the few ports of entry, low wage variation and low growth of this HRM system. Cluster 2, the spot market system, has a very high average value on ports of entry, and low values for performance incentives and hiring rate, which is as expected. Cluster 3, the spot-market with rewards system has high turnover rate, high performance incentives and high wage growth, and a low value for early sorting, which indicates that the performance incentive or tournament does not take place until after the first two years and that the "losers" tend to leave. Cluster 4, performance-based ILM, has extremely high early matching, low performance incentives, and low wage growth, which is consistent with a workers being selected for career development during the first two years and then earnings paths diverge. The turnover rate mean combines the low turnover rate at two years and as well as the high turnover rate at five years.

As demonstrated in Table 2, firms with different R&D levels exhibit differences in HRM practices. We further summarize the components by presenting component means by R&D level for high-educated workers. Table 7 demonstrates that relative to low R&D firms, high R&D firms exhibit higher values for ports of entry, turnover, wage growth, hiring rate, and early sorting. These differences are consistent with the suggestion that high R&D firms are more likely to implement an HRM system that allows flexibility in hiring and retention.

We repeat principal component analysis for low educated workers. In Table 8 we present the component matrix for low educated workers. As with high education workers, similar "ports of entry", "wage growth", and "hiring rate" components appear for the low education HRM variables. The component corresponding to "performance incentives," however, reflects higher variance in wages for 2^{nd} and 5^{th} year-tenure workers, which reflects performance-based pay. This is the lead component. Turnover rates earlier in a worker's career and turnover later in a worker's career appear as separate components, and firm practices vary across these two dimensions for low education workers. Subject to a .50 threshold test for significance, each HR variable has a significant loading in exactly one of these six components. For disclosure reasons we are unable to report component means by clusters or R&D levels for low education workers.

5.3 Worker Productivity Regressions

Next, we map the HRM variables for each firm to continuous variables corresponding to the components identified above, 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 and product market at the 4-digit SIC. 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 estimate separate regressions for low education and high education workers. We use the components as regressors instead of the underlying HRM variables, which tend to be highly correlated by type of practice, to facilitate interpretation.

For the high education HRM components, we observe that several HRM components are related to worker productivity (see Table 9). In support of Hypothesis 1A, firms with multiple ports of entry, which facilitate the hiring of workers with required skills, have higher labor productivity. As hypothesized, this effect is more important (and significant) in the high R&D firms. Firms with performance incentive mechanisms appear to have higher labor productivity, which supports Hypotheses 1B and 2A. This appears to be significant for both low and high R&D firms, with the coefficient on performance incentives for low R&D firms higher than the coefficient for high R&D firms. Performance-based pay appears to be even more important in low R&D firms than in high 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, supporting Hypothesis 1B but not Hypothesis 2B. The effect of turnover rate on worker productivity appears to only be significant for high R&D firms, supporting Hypothesis 2B. Since these statistical relationships have not controlled for firms growing or shrinking, separation rates and hiring rates may reflect poor performing firms losing workers and high performing firms adding workers.[3]. Note that wage growth and early sorting for high educated workers do not seem to be related to productivity.

In Table 10, we present the regression results for low education HRM components. Examining the impact of HRM components of low-education workers, we observe that the existence of performance incentives for both high- and low- R&D firms correspond to higher firm performance, with the effect greater for high R&D firms. These results support hypotheses 1B and 2A. Separation rates vary in their relationship with productivity in high R&D firms according to the timing of the separation. Early turnover corresponds strongly to lower productivity, and late turnover is neutral. These results partially support Hypothesis 1B, in that early retention seems to matter. However, long-run retention does not appear to matter for low educated workers. Separation rates do not appear related to productivity in low R&D firms, which does not support Hypotheses 1B and 2B for low educated workers. Note that ports of entry are not significantly related to productivity, which does not support Hypothesis 1A for low educated workers, so that firms' ability to hire workers by their skills and experience does not seem to matter at the low end of the skill spectrum. We also observe that higher hiring rates for high R&D firms appear to correspond to higher firm performance, although not for low R&D firms. This may reflect that high R&D firms are both more productive and growing more than low R&D firms.

Overall the regression results provide some preliminary evidence against hypotheses 1C and 2C. Contrary to hypothesis 1C, the analysis suggests that the performance-based ILM outperforms the spot market with rewards system for high R&D firms, since turnover corresponds to lower productivity, which is the main differentiator of the two types of systems, since both systems require multiple ports of entry and performance incentives. ILMs rely upon salary schedules to maintain norms of fairness and to lower turnover, while the spot market attempts to replicate opportunity wages and does not attempt to reduce turnover except for the few selected workers who receive the

[3] Note that bootstrapped standard errors and pair-wise significance tests are forthcoming, along with controls for firms growing or shrinking.

highest rewards (i.e. win the tournament). For low R&D firms, performance incentives appear to be the only HRM practice associated with productivity, and so we cannot distinguish between the relative performance of the performance-based ILM and the spot market with rewards. Further analysis will include a more rigorous test of this hypotheses accounting for bundling of HRM practices.

6. Discussion and Future Work

This paper has examined the relationship between firms' technology investment decisions, HRM practices, and productivity. Our preliminary results indicate that 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 with performance incentives. These results indicate that high R&D firms are more likely to buy new skills compared to low R&D firms, and yet these high R&D firms suffer if they lose too many experienced workers. Although the results on the relationship of hiring rate and turnover on firm performance may just capture whether firms are shrinking or growing, the differences in impact across R&D levels can not be fully explained by this.

In support of the assumption that the costs of training workers to acquire new skills associated with a technological leap are proportional to the size of the innovation, while the costs of hiring workers with the necessary skills are invariant to the size of the innovation, we find that high R&D firms are more likely to implement HRM systems consistent with buying new skills than low R&D firms.

A strength of this research is the richness of the data set. There is very little research that ties firm level HRM systems to performance outcomes: the LEHD data allows us to begin analyzing systems and outcomes within firms for a large sample of firms. While the LEHD data provide ample sample sizes and longitudinal variation, the lack of direct measures of worker's skills or occupation and of technological change constrains the statistical estimation and limits our interpretation of the results.

Next steps include implementation of bootstrapping to correctly estimate standard errors of regressions with principal components, inclusion of additional measures of HRM practices and measures of firm performance and productivity, controls for whether a firm is growing or shrinking, and tests of different specifications with a focus on the measurement of synergies between HRM components, and robustness tests covering different methodologies.

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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Table 1. HRM System Clusters for High Education Workers

Variable	Cluster 1 Bureaucratic ILM	Cluster 2 Spot Market	Cluster 3 Spot Market w/Rewards	Cluster 4 Performance-Based ILM	Residual Firms	Sample
Accession rate	0.14	0.13	0.14	0.15	0.22	0.14
	(0.09)	(0.09)	(0.09)	(0.10)	(0.14)	(0.09)
Ratio of mean initial wage to market initial wage	0.70	1.12	0.83	0.97	1.02	0.82
	(0.26)	(0.34)	(0.35)	(0.41)	(0.41)	(0.34)
Std. dev. of initial earnings	4,858	13,923	7,622	6,927	9,318	7,331
	(2,531)	(8,155)	(4,453)	(6,067)	(5,806)	(5,899)
Separation rate at 2 years tenure	0.41	0.44	0.47	0.39	0.48	0.43
	(0.19)	(0.20)	(0.18)	(0.21)	(0.18)	(0.20)
Within job wage growth at 2 years tenure	0.06	0.06	0.07	0.05	0.06	0.06
	(0.07)	(0.06)	(0.06)	(0.09)	(0.06)	(0.07)
Std. dev. of wages at 2 years tenure	4,917	5,303	5,530	25,601	8,718	5,937
	(3,587)	(3,039)	(3,747)	(11,260)	(5,449)	(5,584)
Separation rate at 5 years tenure	0.42	0.43	0.46	0.49	0.48	0.43
	(0.17)	(0.19)	(0.17)	(0.20)	(0.19)	(0.18)
Within job wage growth at 5 years tenure	0.03	0.02	0.04	0.02	0.06	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Std. dev. of wages at 5 years tenure	6,133	6,778	18,672	7,196	79,100	10,540
	(2,906)	(2,776)	(6,987)	(4,398)	(31,481)	(14,681)
N	425	149	116	26	23	739

Notes: Table shows within-cluster means. Standard deviations in parentheses.

Table 2. High Education HRM Cluster Sizes by Firm R&D Level

	Low R&D Firms		High R&D Firms	
Cluster 1: Bureaucratic ILM	197	(65.2%)	228	(75.5%)
Cluster 2: Spot Market	38	(12.6%)	111	(36.8%)
Cluster 3: Spot Market w/Rewards	47	(15.6%)	69	(22.8%)
Cluster 4: Performance-Based ILM	15	(5.0%)	11	(3.6%)
Residual Firms	5	(1.7%)	18	(6.0%)

Notes: Column percentages given in parentheses. See text for definition of clusters.

Table 3. HRM System Clusters for Low Education Workers

Variable	Cluster 1 Bureaucratic ILM	Cluster 2 Spot Market	Cluster 3 Performance-Based ILM	Cluster 4 Spot Market w/Rewards	Residual Firms	Sample
Accession rate	0.17	0.20	0.23	0.29	0.27	0.18
	(0.10)	(0.12)	(0.14)	(0.17)	(0.15)	(0.11)
Ratio of mean initial wage to market initial wage	1.04	1.18	1.60	1.38	1.56	1.07
	(0.40)	(0.48)	(0.40)	(0.41)	(0.37)	(0.42)
Std. dev. of initial earnings	4,827	5,319	9,980	7,594	7,968	4,994
	(3,830)	(3,189)	(7,276)	(3,852)	(2,204)	(3,808)
Separation rate at 2 years tenure	0.47	0.47	0.37	0.47	0.55	0.47
	(0.17)	(0.19)	(0.12)	(0.21)	(0.25)	(0.17)
Within job wage growth at 2 years tenure	0.07	0.07	0.07	0.12	0.14	0.07
	(0.07)	(0.07)	(0.04)	(0.09)	(0.00)	(0.07)
Std. dev. of wages at 2 years tenure	4,051	4,792	6,868	6,715	34,574	4,309
	(3,322)	(3,123)	(4,267)	(3,674)	(3,748)	(3,681)
Separation rate at 5 years tenure	0.48	0.49	0.46	0.59	0.64	0.48
	(0.16)	(0.17)	(0.08)	(0.16)	(0.13)	(0.16)
Within job wage growth at 5 years tenure	0.03	0.04	0.06	0.07	0.06	0.03
	(0.03)	(0.04)	(0.02)	(0.03)	(0.06)	(0.03)
Std. dev. of wages at 5 years tenure	4,131	12,489	213,728	51,455	23,043	7,859
	(1,703)	(6,173)	(187,269)	(11,967)	(3,992)	(25,090)
N	612	116	5	11	3	747

Notes: Table shows within-cluster means. Standard deviations in parentheses.

Table 4. Explained Variance by HRM Components

	High Edu		Low Edu	
	% of variance explained	Cumulative explained variance	% of variance explained	Cumulative explained variance
Component 1	0.268	0.268	0.279	0.279
Component 2	0.173	0.441	0.185	0.465
Component 3	0.134	0.575	0.159	0.624
Component 4	0.108	0.683	0.136	0.760
Component 5	0.087	0.770	0.092	0.852
Component 6	0.080	0.850	0.060	0.912
Component 7	0.056	0.906	0.052	0.963
Component 8	0.051	0.957	0.024	0.987
Component 9	0.043	1.000	0.013	1.000

Notes: Variance explained by relative weights of each factor's eigenvalues from a principal components analysis.

Table 5. HRM Component Patterns For High Education Workers

Variable:	Component 1 Ports of Entry	Component 2 Turnover Rate	Component 3 Performance Incentives	Component 4 Wage Growth	Component 5 Hiring Rate	Component 6 Early Sorting
Accession rate	0.06	0.18	0.05	0.03	**0.95**	0.02
Ratio of mean initial wage to market initial wage	**0.85**	0.13	0.05	-0.02	0.03	0.23
Std. dev. of initial earnings	**0.86**	0.05	0.18	0.04	0.06	-0.11
Separation rate at 2 years tenure	0.03	**0.91**	0.05	0.02	-0.01	-0.12
Within job wage growth over first 2 years tenure	-0.02	-0.01	0.01	**0.96**	-0.02	0.06
Std. dev. of wages at 2 years tenure	0.07	-0.01	0.19	0.06	0.02	**0.94**
Separation rate at 5 years tenure	0.19	**0.76**	-0.02	-0.05	0.32	0.17
Within job wage growth over first 5 years tenure	0.17	-0.02	**0.62**	**0.52**	0.27	-0.02
Std. dev. of wages at 5 years tenure	0.15	0.04	**0.90**	-0.05	-0.04	0.23

Notes: Component pattern matrix from the top 6 components of a principle components analysis with varimax rotation. Weights ≥ .50 are boldfaced.

Table 6. High Education Component Means for High Education HRM Clusters

		Cluster 1 Bureaucratic ILM	Cluster 2 Spot Market	Cluster 3 Spot Market w/Rewards	Cluster 4 Performance-Based ILM	Residual Firms
Component 1:	Ports of Entry	-0.274	0.572	-0.079	0.103	0.028
Component 2:	Turnover Rate	-0.080	0.020	0.214	-0.001	0.211
Component 3:	Performance Incentives	-0.116	-0.327	0.151	-0.513	1.359
Component 4:	Wage Growth	-0.004	-0.050	0.139	-0.165	-0.028
Component 5:	Hiring Rate	-0.011	-0.223	-0.039	0.072	0.630
Component 6:	Early Matching	-0.144	-0.017	-0.134	1.574	-0.029
N		425	149	116	26	23

Notes: See text for definition of clusters and components.

Table 7. High Education HRM Component Means by Firm R&D Level

		Low R&D Firms	High R&D Firms
Component 1:	Ports of Entry	-0.248	0.086
Component 2:	Turnover Rate	-0.024	0.014
Component 3:	Performance Incentives	-0.096	-0.077
Component 4:	Wage Growth	-0.057	0.045
Component 5:	Hiring Rate	-0.132	0.032
Component 6:	Early Matching	-0.139	0.006
N		302	437

Notes: See text for definition of components.

Table 8. HRM Component Patterns for Low Education Workers

Variable:	Component 1 Performance Incentives	Component 2 Ports of Entry	Component 3 Wage Growth	Component 4 Hiring Rate	Component 5 Early Turnover	Component 6 Late Turnover
Accession rate	0.06	-0.01	0.11	**0.97**	0.04	0.12
Ratio of mean initial wage to market initial wage	0.15	**0.92**	0.01	0.01	-0.10	0.08
Std. dev. of initial earnings	0.00	**0.95**	0.04	-0.01	0.05	0.00
Separation rate at 2 years tenure	0.05	-0.04	-0.02	0.04	**0.97**	0.21
Within job wage growth over first 2 years tenure	0.00	-0.02	**0.93**	-0.05	-0.03	-0.06
Std. dev. of wages at 2 years tenure	**0.95**	0.09	0.14	0.04	0.01	0.07
Separation rate at 5 years tenure	0.07	0.07	0.00	0.13	0.22	**0.96**
Within job wage growth over first 5 years tenure	0.30	0.09	**0.72**	0.31	0.02	0.10
Std. dev. of wages at 5 years tenure	**0.96**	0.06	0.07	0.05	0.05	0.02

Notes: Component pattern matrix from the top 6 components of a principle components analysis with varimax rotation. Weights ≥ .50 are boldfaced.

Table 9. High Education HRM Components on Firm Performance

	(1)		(2)	
Intercept	2.1152		2.1649	
	(0.2641)	***	(0.2672)	***
ln(K/L)	0.2978		0.2971	
	(0.0303)	***	(0.0305)	***
C1: Ports of Entry	0.0739			
	(0.0268)	**		
C1 × Low R&D			0.0340	
			(0.0328)	
C1 × High R&D			0.1323	**
			(0.0537)	
C2: Turnover rate	-0.0492	*		
	(0.0264)			
C2 × Low R&D			0.0070	
			(0.0408)	
C2 × High R&D			-0.0753	**
			(0.0346)	
C3: Performance Incentives	0.0800	**		
	(0.0265)			
C3 × Low R&D			0.2072	
			(0.0968)	**
C3 × High R&D			0.0783	
			(0.0301)	**
C4: Wage growth	-0.0042			
	(0.0247)			
C4 × Low R&D			-0.0177	
			(0.0345)	
C4 × High R&D			0.0154	
			(0.0358)	
C5: Hiring rate	0.0302			
	(0.0259)			
C5 × Low R&D			0.0473	
			(0.0567)	
C5 × High R&D			0.0285	
			(0.0291)	
C6: Early matching	0.0303			
	(0.0252)			
C6 × Low R&D			0.0619	
			(0.0906)	
C6 × High R&D			0.0297	
			(0.0276)	
R^2	0.66		0.66	
N	760		760	

Notes: Dependent variable is log worker productivity. Both specifications include controls for 4-digit SIC. Standard errors in parentheses.
* Denotes significance at the 10% level
** Denotes significance at the 5% level
*** Denotes significance at the 1% level

Table 10. Low Education HRM Components on Firm Performance

	(1)		(2)	
Intercept	2.2624		2.0525	
	(0.2389)	***	(0.2725)	***
ln(K/L)	0.3097		0.3090	
	(0.0300)	***	(0.0302)	***
C1: Performance incentives	0.0638			
	(0.0251)	**		
C1 × Low R&D			0.0516	
			(0.0262)	**
C1 × High R&D			0.2440	
			(0.1124)	**
C2: Ports of entry	0.0313			
	(0.0246)			
C2 × Low R&D			0.0186	
			(0.0301)	
C2 × High R&D			0.0605	
			(0.0433)	
C3: Wage growth	0.0225			
	(0.0245)			
C3 × Low R&D			0.0129	
			(0.0345)	
C3 × High R&D			0.0516	
			(0.0350)	
C4: Hiring rate	0.0475			
	(0.0258)	*		
C4 × Low R&D			0.0528	
			(0.0488)	
C4 × High R&D			0.0587	
			(0.0306)	**
C5: Early turnover	-0.1038			
	(0.0250)	***		
C5 × Low R&D			-0.0491	
			(0.0413)	
C5 × High R&D			-0.1263	
			(0.0316)	***
C6: Late turnover	-0.0083			
	(0.0268)			
C6 × Low R&D			0.0212	
			(0.0436)	
C6 × High R&D			-0.0279	
			(0.0334)	
R^2	0.66		0.66	
N	760		760	

Notes: Dependent variable is log worker productivity. Both specifications include controls for 4-digit SIC. Standard errors in parentheses.
* Denotes significance at the 10% level
** Denotes significance at the 5% level
*** Denotes significance at the 1% level