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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 sample of electronics firms in seven large states from a newly developed employer-employee matched database (Longitudinal Employer Household Dynamics, LEHD), we examine the relationship of human resource management (HRM) practices, technology and worker productivity. The empirical results indicate strong clustering of HRM practices across firms, with high technology firms more likely to implement spot labor market practices than lower technology firms. Further, principal component regressions demonstrate that high technology firms have higher worker productivity if the firms implement spot market practices while low technology firms have higher worker productivity if they implement internal labor market practices. These findings are consistent with a "make vs. buy" model of workforce skill adjustment.

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 paper is to first examine the relationship between firm-level technological advancement (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 second, examine how this relationship is connected to firm performance.

Although the relationship of technological change and labor market outcomes at the individual 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. Early studies using the Current Population Survey documents shifts in wage levels that are consistent with the hypothesized effects of skill-biased technological change for individuals (Bound and Johnson, 1992; Levy and Murnane, 1992; Katz and Murphy, 1992; and Juhn, Murphy and Pierce, 1993). Building on the individual-level analysis, Berman, Bound, and Griliches (1994), and Allen (1997) find support for a strong connection between compensation and technology use at the industry-level. However, there is little large-scale work looking at the relationship of technology and labor market outcomes within firms.

Combining firm-level technology data and individual-level labor market data allows an analysis of firms' technology and HRM decisions. At the firm-level, Doms, Dunne, and Troske (1997), and Jensen and Troske (1997) use the Longitudinal Research Database (LRD) to study changes in wage distributions at the plant level and find a strong relationship between technology investment and worker skill at the plant level. Black and Lynch (2001) use the LRD linked with a nationally representative survey of work practices 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. Once the relationship of technology and human resources practices at the firm level is established, we can then examine potential mechanisms underlying the relationship.

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

One mechanism through which the observed shifts in wage structures at the individual level 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 on workers wages, with several significant caveats[2].

Another channel that technology can impact individual 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.

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). Also, firms' product strategies directly affect both their technology choices and their HRM choice (Lazear, 1998; and Baron and Kreps, 1999)

Building on the technological change literature, we propose a channel connecting technology and HRM practices at the firm level that ties the individual-skill bias approach and the organization change approach together. We propose a "make versus buy" model of workforce skill adjustment. 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. 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 necessary skills in-house or they can structure their HRM practices to attract and retain workers with the necessary skills on the external market.

After documenting the technology-HRM relationship we can then examine the connection of technology outcomes and HRM outcomes on firm performance. Previous analysis of the relationship between HRM and performance focused on a 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;

[2] 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.

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). This project connects these micro and macro approaches by using data that allows us to capitalize on the strengths of each type of research. Data from the Longitudinal Employer-Household Dynamics (LEHD) Program enable us 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 linked employer-employee data to examine the HRM-technology-productivity relationship for surviving firms 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. 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.

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-education and low-education 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.

First, we document the HRM systems observed in our sample. Implementation of HRM systems is more important than implementation of 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. 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 across firms in this industry. HRM bundles appear to span 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 there are large differences in the impact of human resource practices on labor productivity across levels of technological investment and that for firms with high levels of R&D, HRM practices for high-education workers associated with having multiple ports of entry, a high hiring rate[3], and awarding performance incentives are positively related to worker productivity. High R&D firms implementing HRM systems for low-education workers with performance incentives, high hiring rate, and low turnover have higher productivity. For low R&D firms, high-education HRM practices that demonstrate performance incentives are positively related to productivity, while for low-education 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 our "make versus buy" model of workforce skills, where 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 describes a mechanism 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 statistical results on firm performance, HRM, and R&D that are consistent with our proposed mechanism. Finally, we conclude with a summary and a discussion of the implications of the research.

3. 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 mechanism that might explain the diversity. The underlying concept of the model is that HRM practices affect the cost structure of how firms adjust the skills of their workforce.

[3] 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.

If technological investment is complementary to adjusting the workforce skills, firms HRM decisions and R&D decisions will be related.

Since we are analyzing only the high-tech electronics sector, we focus on the variation of the speed of technological change over time across 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 increased 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 is hired and developed 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 and 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.

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 adjustment cost 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 present 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). 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

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 workers.*

If worker costs of retraining increases proportionally with size of technological change (as proxied by R&D), and firm hiring adjustment 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.*

Firms with low R&D benefit from experienced workers' knowledge gained from learning by doing, which will increase the worker productivity.

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 create 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.[4] 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 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.

[4] 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.

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 within job wage growth for workers with 2 years experience: Standard deviation of wage growth between 1995 and 1997 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 within job wage growth for workers with 5 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. Optimally, with a longer time span of data, we could measure how HRM practices change with technological investment change. However given the restrictions of the data, we can only examine one cross section of the data (where 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. In this paper, we focus only on knowledge workers, and use imputed education values developed by the LEHD staff to distinguish knowledge workers from other types of workers[5]. In this paper we empirically examine 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. However, R&D may be a good proxy for picking up firm's ability to learn and develop new knowledge (Cohen and Levinthal, 1999). 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

[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 importantly earnings, industry, geography, gender and 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.

differentiate firms' HRM systems, and the relationship of these components to 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 implement a principal components regression to examine the statistical relationship of worker productivity with HRM practices for different technology paths.

5.1 HRM Cluster Descriptions

Firms implement HRM practices in bundles, and we anticipate a high-level of correlation of adopted bundles across firms. 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.

In Table 1, we present results from examining the HRM variables for high-education workers. Summary statistics of the first four clusters of HRM practices are reported. The last group of firms represents the aggregation of multiple small clusters that are not disclosable according to Census Bureau confidentiality requirements.

The basic characteristics of the clusters, along with assigned names, as as follows:

- <u>Cluster 1 (Skills-based ILM)</u>: Firms hire less experienced workers, so average initial earnings and standard deviation are below average, and workers receive steady earnings growth and have low turnover. 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.

- Cluster 2 (Spot Market): Firms tie worker's pay to the external labor market. Firm can identify workers' talents and skills, and hire and pay accordingly (matching is good). Firm 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.

- Cluster 3 (Bureaucratic ILM): Firms have very low initial earnings with very low standard deviation, which indicates they hire younger workers and provide steady wage growth, and workers have low turnover. 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.

- Cluster 4 (Spot Market with Tournament): Firms have high initial earnings with large variance, which indicates that the firms hires experienced workers and provides below-average earnings growth, and workers have high turnover. 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 higher than in spot market. Firm must include performance rewards and tournament or wage-efficiency type incentives, thus variance of earnings growth is high. Earnings growth is higher than in spot market. Early separation rate is higher than in spot market since the bad matches (both at hire and in rewards) end.

Firms are concentrated in clusters 1 (37%) and 3 (32%), and so 69% of all firms have some type of ILM system. Only 16% of firms are in cluster 2, and 8% in cluster 4, and so 24% of all firms have some type of Spot Market system. The primary variables that differentiate HRM systems appear to be initial earnings (average and standard deviation) and wage growth during the first two years.

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 industry mean, and then present the cluster sizes of HRM practices for high-education workers at different levels of R&D. Within each R&D bracket, we observe different distributions of firms across the HRM clusters. 81.7% of low R&D firms are in clusters 1 and 3, while 59.6% of high R&D firms are in clusters 1 and 3. This is preliminary evidence that the high R&D firms are more likely to implement external labor market-based hiring and compensation practices than low R&D firms.

5.2 HRM Principal Components Analysis

As demonstrated earlier, firms adopt discrete bundles of HRM variables; as a result, 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. 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 then use the principal components as the independent variables in an ordinary least squares regression[6].

In Table 3, we present a summary of the variance explained by each set of components. Each value in the table represents a proportion of the eigenvalue from each corresponding principal component. We present results for the set of nine HRM measures for high-education workers. Each HRM component has one or two variables that distinguish it. For the subsequent analysis we focus on the first six components, which explain 84% of the variance for the set of HRM variables.

The first six components from the principal components analysis were orthogonally transformed through a varimax rotation. Table 4 reports the rotated component pattern matrix for high-education 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 component 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-education workers after two and five years of tenure. The third component, labeled “wage growth” reflects high levels of within-job wage growth at both the second and fifth years of tenure. The fourth component, “hiring rate” simply reflects the overall hiring rate in 1997. The fifth component, “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 sixth component, “early matching” 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 exactly one component.

[6] Detailed descriptions of the technique are given in e.g. Sen, Srivastava (1990) 253-255, or Draper and Smith (1981) 327-332. 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.)

In Table 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. Cluster 1, the skills-based ILM system, has relatively low values on turnover rate and wage growth, and relatively high value on hiring rate. Cluster 2, the spot-market system has mid-range values on all components. Cluster 3, bureaucratic ILM, has relatively low values on ports of entry, turnover rate, and early matching, and has relatively high values on wage growth and performance incentives. Cluster 4, the spot market with tournament, has relatively high values on ports of entry, turnover rate, and early matching, and relatively low values on wage growth, hiring rate and performance incentives. The component scores are consistent with our labeling of the clusters.

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-education workers. Table 6 demonstrates that relative to low R&D firms, high R&D firms exhibit higher values for ports of entry, turnover rate, wage growth, hiring rate, and early matching and lower value for performance incentives. 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, retention, and workforce development. Low R&D firms are more likely to implement ILM systems with performance incentives.

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, measured as log worker productivity. We control for log of physical capital (in order to capture capital intensity) and product market at the 4-digit SIC (in order to capture product lifespan differences). We estimate two specifications: specification one has no R&D interactions, and specification two includes interactions of R&D categories (high, low) with the HRM components. We employ principal components as regressors instead of the underlying HRM variables because of multicollinearity and latent concerns.

We observe that only two HRM components, ports of entry and turnover rate, are significantly related to worker productivity across all firms in the industry (see Table 7). In support of Hypothesis 1A, firms with multiple ports of entry, which facilitate the hiring of workers with required skills, have significantly higher labor productivity. As hypothesized, this effect is more important (and significant) in the high R&D firms. As hypothesized for both high and low R&D firms, firms with higher turnover rates have significantly lower labor productivity. This effect is more important (and significant) in the high R&D firms, which supports Hypothesis 1B but not 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.

Two other HRM components, performance incentives and early matching, are significant when interacted with R&D. High R&D firms with performance incentives appear to have higher labor productivity, which supports Hypotheses 1B. However performance incentives were hypothesized to go with higher productivity in both high and low R&D firms, and the hypothesized relationship is observed only for high R&D firms and is not significant for low R&D firms (hypothesis 2A not supported). Firms with early matching, or a large standard deviation of earnings growth in the first two years, appear to have significantly lower worker productivity for low R&D firms, which was not expected. To the extent that early matching indicates the firm's HRM system is not an ILM, then this result indicates that lower productivity is associated with more spot-like HRM system, which is consistent with hypothesis 2C.

Overall the regression results provide some preliminary evidence against hypotheses 1C. 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 highest rewards (i.e. win the tournament). For low R&D firms, we have a mixed result, since coefficients on ports of entry and early matching suggest Spot Market and ILM systems, respectively, have better firm performance. Further analysis will include a more rigorous test of these hypotheses.

6. Discussion

This paper presents evidence of the relationship between firms' technology investment decisions, HRM practices, and productivity. We find that there is a positive correlation between performance and *buying* new skills for both high and low R&D firms, although the estimated relationship is higher for high R&D firms. However experienced workers seem to be important for high R&D firms, since turnover rates for high R&D firms are negatively correlated with labor productivity. Labor productivity is also positively correlated with performance incentives for high R&D firms. We interpret these results for high R&D firms to indicate that an HRM system that segments high-education workers into two tiers within a few years of employment, with career development and higher earnings trajectory for the workers in the top tier, will be better performing than firms that apply a uniform ILM or spot market to all high-education workers.

Although low R&D firms seem to perform better with an HRM system that has multiple ports of entry, differential earnings growth of workers within the first two years goes with lower labor productivity. This indicates that productivity of low R&D firms goes with ILM systems that allow flexible ports of entry.

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 multiple ports of entry without early matching. 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 cannot be fully explained by this.

Contrary to our hypotheses, labor productivity in both high and low R&D firms is associated with using ILM-style HRM systems for high-education workers. These ILM systems seem to have different characteristics in the high and low R&D firms: higher productivity in the high R&D firms seems to go with segmenting workers within a few years of hire into two tiers with career development and higher earnings for the top tier; higher productivity in the low R&D firms seems to go with treating workers basically the same for the first two years after hire. Overall our results indicate that high R&D firms seem to perform better with an HRM system that applies an ILM system to the top performers and spot-market HRM to other workers over time, and that low R&D firms seem to perform better by being flexible in hiring workers into an ILM system.

A strength of this research is the richness of the data set: the LEHD data allow us to analyze a firm's HRM system and performance 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.

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 and is mediated through the firm's HRM system, 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 Practice Clusters for High Education Workers

Variable	Cluster 1 Skills-Based ILM	Cluster 2 Spot Market	Cluster 3 Bureaucratic ILM	Cluster 4 Spot Market w/Tournament	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)
Std. dev. 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)
Std. dev. 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)
Std. dev. 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. 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	120	(16.2%)	153	(20.6%)
Cluster 2: Spot Market	34	(4.6%)	86	(11.6%)
Cluster 3: Spot Market w/Tournament	125	(16.9%)	110	(14.8%)
Cluster 4: Performance-Based ILM	8	(1.1%)	49	(6.6%)
Residual Firms	13	(1.8%)	43	(5.8%)

Notes: Percent of total given in parentheses. See text for definition of clusters.

Table 3. Explained Variance by HRM Components

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

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

Table 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
Std. dev. 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
Std. dev. 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
Std. dev. 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 6 components of a principle components analysis with varimax rotation. Weights $\geq .50$ are boldfaced.

Table 5. Component Means for High Education HRM Clusters

		Cluster 1 Skills-Based ILM	Cluster 2 Spot Market	Cluster 3 Bureaucratic ILM	Cluster 4 Spot Market w/Tournament	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.

Table 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.

Table 7. High Education HRM Components on Firm Performance

	(1)		(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 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