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An Empirical Study of Adjustments in Human Resource Systems

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I. Introduction

A well-established observation is that since the early 1980s, the organization of work has changed considerably, generally toward greater decentralization of decision-making and reliance on financial incentives (Appelbaum and Batt, 1994, Appelbaum et al., 2000, Caroli and Van Reenen, 2001). Improved educational attainments may have facilitated decentralization of decision-making, as did computerization (Caroli and Van Reenen, 2001, Autor, Levy, and Murnane, 2003, Bartel, Ichniowski, Shaw, 2005); new technologies may have required greater reliance on employee decision-making (Ben-Ner et al., 2000, Bresnahan, Brynjolfsson, and Hitt, 2002), and the success of Japanese organizational practices and their popularization by the media and academics, plus the concomitant academic research into new forms of organizing work, may have also contributed to the introduction of employee participation in financial rewards and decision-making. Whatever the reasons for these changes, the process of transformation has not been instantaneous; rather, firms adopted and shed practices at an uneven pace. Some researchers commented on why the adoption of useful organizational innovations may be delayed, such as that "old dogs" take longer to learn "new tricks" (Ichniowski and Shaw, 1995, Prendergast and Stole, 1996), but most of the literature focuses on why firms have certain human resource practices and how these practices affect performance (see, for example, Osterman, 1994, Jones and Kato, 1995, Ichniowski, Shaw, and Pernushi, 1997, Cappelli and Neumark, 2001, Bloom, Kretschmer and Van Reenen, 2006), rather than on the process through which they come to adopt those practices. Differences in practices among similar firms situated in similar circumstances at a particular point in time are typically attributed to managers' optimization errors, suggesting that some firms are outside equilibrium.[1] But the question of whether and how these errors are ever corrected is rarely asked, and in the literature on human resource practices it has never been answered. Finding out whether firms make corrections requires an examination of the dynamics of human resource practices, and finding out how they make the corrections requires an investigation into the information and signals managers use and how long it takes them to translate this information into adjustments of human resource practices. In short, it requires a study of how firms behave outside equilibrium, that is, what they learn from their experience and from other sources and how they put into action what they have learned. This is what we set out to understand in this paper. We study learning in the context of human resource practices with the goal of enriching our understanding of organizational learning in general and in the specific context of human resources.

In this paper, we investigate an original and unique dataset to test several theoretical hypotheses about ways in which firms learn how to adjust the structure of their workplace. We study the dynamics of year-to-year choices made by our sample firms in order to understand what determines the adoption of

[1] Bresnahan, Brynjolfsson, and Hitt (2002) discuss this issue when they investigate empirically the determinants of firms' choice of the mix of skilled labor, IT capital, and specific workplace organization practices.

human resource practices across space and time, emphasizing the notion of learning.[2] We envision the process of choice as an executive decision based on what management knows about its own organization and about human resource practices in general. Management's information about both internal resources and the added value of different practices is incomplete, especially during times of change and as new techniques emerge, and therefore learning is central to the process of making decisions. Managers need to learn about their firms' organizational needs, options, and capabilities before making decisions on whether to change their firms' human resource practices, and, if change is indicated, what changes to implement.

Learning is not directly observable. Learning may be investigated by comparing the outcomes of an experimental group assigned to a learning treatment with the outcomes of a control group (as it is done, for example, in the job training literature). This approach is not feasible in many learning situations, including those of organizational learning; instead, researchers make inferences about learning by studying the relationship between its hypothesized determinants and its consequences through a latent variable approach. We develop a framework that identifies the informational determinants of learning and relates them to organizational choices and economic outcomes and then test for the significance of the determinants and outcomes. Following the established literature, we identify: (a) the effects of learning-by-doing through the effects of experience on performance, and additionally on choice of human resource systems, (b) the effects of matching between firm capabilities and organizational needs through the effects of changes in performance on choice of system, and (c) the effects of social learning through the influence of a firm's geographic location and industry-level variables on choice of systems. Our paper is similar to a certain degree to the literature that looks at the determinants of adoption of human resource system and its effect on performance. However, the key difference lies in the fact that the literature on determinants and consequences investigates behavior in equilibrium, whereas we study dynamic out-of-equilibrium behavior and emphasize learning related variables. This is the first paper to evaluate a wide spectrum of variables that influence learning, as well as firm characteristics, and to consider the adoption of human resource practices and their effects on performance from the perspective of learning.

In the middle of the 1990s, we surveyed all publicly-traded and a sample of privately-held Minnesota based firms, asking them to provide the dates of introduction of various human resource practices concerning the group and firm-level decision-making and financial incentives. Following much of the literature, we combined individual practices into systems (sometimes referred to as bundles). Figure 1 documents the significant decline in the proportion of firms with a traditional system of human resources—i.e., a system that combines centralized decision-making with fixed pay. The figure focuses on the publicly-

[2] We are taking our cues from Besley and Case (1993), p. 396, who write: "We are interested in understanding what determines adoption of the technology across space and time." The related but separate question of how organizational innovations are diffused through a population of firms is not investigated in this paper.

traded firms, but the picture is very similar when the privately-held firms are included.[3] It also documents the rise in the proportion of firms that have a group-oriented financial incentives system or a high-performance system that combines decentralized decision-making and financial incentives. The figure reflects the cumulative result of the choices made by each sample firm over time of whether to continue with its current human resources system or switch to another system. Table 1 summarizes these choices annually and shows the disposition of the 855 annual decisions that were made by the sample of publicly-traded firms between 1980 and 1994. A majority of the firms (72.7%) had changed systems during the period under consideration, with some firms undergoing more than one change, for a total of 83 system changes. Most transitions were from the traditional system into the financial incentives system, and from the financial incentives system into the high-performance system. Our empirical investigation examines these choices relative to various signals and information that management may have received prior to making these decisions in order to infer about the process and nature of learning.

Our empirical investigation of the learning process is guided by the learning and technological diffusion literatures, as well as by what we have learned from human resources professionals.[4] Human resource executives tell a multilayered story, which seems to vary with firm size, location, and fortunes, as well as idiosyncratic factors such as the personalities of key executives. The initiative for organizational change often comes from CEOs who are either unhappy with performance and want to shake up the organization or even transform it, or on the contrary, feel that the company is doing so well that it can experiment and take risks with new ideas. Some human resource executives take a strategic view of the organization and are constantly looking for new ideas; they are generally well-connected to their peers and participate in high-level professional meetings with consultants and academics, sometimes as speakers relating their firms' experiences. Some human resource departments, particularly in large firms, have employees with graduate degrees who attend professional conferences and read the professional literature. These employees constitute an internal consulting group that executives can consult in addition to external consultants. In other firms, the human resource employees and executives concentrate on day-to-day functions and have few opportunities to engage in strategic thinking. Most executives tell about "resistance to change," the familiar phenomenon whereby those who anticipate losing from a change oppose it and resist it if they can, and thereby slow the speed of system change.

Executives' accounts of the processes that lead to change or continuity in their firms' human resource systems share some of the central elements represented in the economic literature on learning (e.g., Jovanovic and Nyarko, 1995, 1996, Foster and Rosenzweig, 1995, Ericsson and Pakes, 1998, Cabral

[3] For coherence of presentation and completeness of analysis, we focus the presentation of our findings on the subsample of publicly-traded firms for which financial data are available. Such data are required for testing the matching hypothesis as well as for analyzing the effects of learning on firm performance. Whenever the analysis did not require the use of financial performance, we replicated the estimations for the full sample of firms. The main results are shown in Appendix Table 2.

[4] As professors of human resources and industrial relations, we have had numerous interactions with human resources professionals. One of us has belonged for a long time to a membership organization of human resource executives in medium and large-sized organizations created to facilitate networking and learning.

and Leiblein, 2001, and Munshi, 2004). This literature studies various forms of learning, often in the context of the suitability of a technology for deployment in an organization, and emphasizes the dynamic process as it unfolds over time. The three dominant theoretical approaches include the familiar *learning-by-doing* theory, whereby decision-makers learn from their experience to improve their ability to operate a system; the *matching* theory, according to which decision-makers extract information about their firm's capabilities for suitability with what is needed to operate a particular system; and the *social learning* theory, which suggests that decision-makers learn from observing the behavior of others.

We build on these theories and on practitioners' insights to investigate possible influences on changes that firms made in their human resource systems. The ambit of our investigation is broader than that of other studies of learning, in that we approach the question of how firms learn from a broad conceptual perspective, allowing for the possibility that firms may learn in multiple ways and from diverse sources, and our rich dataset allows us to investigate multiple ways and sources of learning. We evaluate whether experience with a particular system tends to deepen a firm's commitment to that system or facilitates its transition to more complex systems, and examine how firm performance evolves with accumulated experience with a system, both key predictions of learning-by-doing. We also investigate how firms use information about their own performance to inform their choices of human resource systems, a prediction of learning from the matching theory literature. Furthermore, in relation to the social learning literature, we study whether information about the behavior of other firms, possibilities of networking, and geographic location influence a firm's choice of human resource systems. Finally, we examine the effect of factors such as firm age, size, and geographic location on the speed of learning and adoption of human resource systems.

Our principal dataset is rich, containing 110 publicly-traded firms over a period of up to 15 years. The fact that we use data on firms from a single state removes some of the heterogeneity found in large national datasets. The relatively small sample size may generate imprecise findings, which makes it harder not to reject the null hypothesis of zero effects. The finding of systematic effects would therefore suggest that the learning processes that we uncover in this paper have a significant impact on firms' behavior. The paper contributes to the theory of organizational learning by developing a conceptual framework that allows us to combine different modes of learning and test empirically the importance of different factors for learning about human resource systems. Our findings suggest a multifaceted learning process. Learning-by-doing leads firms to stay with their current system for a few years until their accumulated experience is large enough to implement and be more productive with a more complex system. It takes about 12 years for a firm with a traditional system to transition to the high-performance system whereas firms with the decision-making or financial incentive systems wait only about 3 years to switch to the more complex system. Firms' recent performance tends to be used as a signal of whether they should switch systems, in an expected fashion: decline in performance is associated with a lower likelihood of taking up a more complex system, whereas improvement in performance is associated with a greater tendency to move to a more complex system. Finally, firms learn from their peers and others, and we find a significant influence from what and how others behave on a firm's decision to adjust its system. Different learning mechanisms work in a complementary fashion, and their influence varies with the nature of the transition. Firms seem to move from the traditional system into the high-performance system in two stages: first they move into an intermediate system (decision-making or financial incentives) on the basis of social learning as well as some confirmation that they have the requisite organizational capabilities, and second, they transition from an intermediate system to the full high-performance system on the basis of stronger confirmation of their organizational capabilities and information about desirable performance by firms with the high-performance system.

The organization of the paper is as follows. In the next section, we develop the conceptual framework for studying learning by organizations and offer the main hypotheses. In section III, we describe the data, and in section IV, we put forth our analytical framework and empirical strategy. The results are described in section V, and in section VI, we conclude the paper with a discussion of the implications of our findings for the understanding of learning by organizations as well as for further research.

II. Learning by Organizations: A Conceptual Framework

The organization that succeeds in extracting better, smarter, and more economical effort from its employees will, *ceteris paribus*, perform better than other organizations. To accomplish this, a certain set of human resource practices must be put in place relative to an organization's specific needs and capabilities. However, managers do not always know how to accomplish that because (a) they do not fully know their organizations' capabilities, (b) those capabilities may not be sufficient relative to organizational needs, (c) managers have only an imperfect understanding of the options available to their organization, (d) they may not know what works best for their organization, and (e) the environment changes continuously, so what worked well yesterday may not work as well tomorrow. As a result, how an organization manages its affairs has to be evaluated frequently in response to new understandings and new information. Because the payoff for doing things right in a competitive environment is high, and the penalty for doing things wrong is severe, organizations have an incentive to learn how to do things right. This is the basis of the economic approach to learning.

Three different approaches to learning have been developed in the literature, although it is plausible that an individual or a group may engage in more than one form of learning. The first approach emphasizes the accumulation of capabilities through experience; this is the learning-by-doing theory. The second approach focuses on the accumulation of information about the firm's capabilities; this is the matching theory of learning. The third approach concentrates on how a firm observes what other firms do and draws inferences about what may be useful to emulate; this is the social learning theory. The mode of learning and the combination of sources from which information is drawn are likely to depend on the object of learning; the process of learning about production technologies possibly differs from the process of learning about organizational technologies. Since our concern in this paper is with human resource systems, we develop the three approaches with reference to learning about them.

We classify human resource systems relative to the allocation of decision-making and of financial returns as the central elements of organizational structure (e.g., Hart and Moore, 1990) and distinguish among four systems on the basis of their reliance on employee involvement in decision-making through teamwork and similar mechanisms, and reliance on group or firm-level incentives such as group bonus, profit sharing, and employee stock ownership. The four systems are the *traditional system*, which entails centralized decision-making and fixed pay; the *decision-making system*, which implements decentralization of decision-making via employee involvement but is associated with fixed pay; the *financial incentives system*, which relies on group and firm-level financial incentives but not employee involvement in decision-making; and the *high-performance system*, which combines the decision-making and financial incentives systems. This classification is summarized in Figure 2. Moving away from the traditional system entails a move to a more complex human resource operation.

The early 1980s saw the introduction of new systems of work organization. In a majority of firms, the long-standing human resource system that prevailed in the United States at the time was the traditional system. Under the traditional system, employees have little control over how their work is done, work according to rules and procedures established by superiors, operate under close supervision, and are compensated through fixed wages that change over time primarily as a function of an employee's tenure. Since the early 1980s, novel ways of motivating, compensating, and coordinating employees have been introduced. These include greater reliance on employees to make decisions, and making part of employees' compensation dependent on group or firm results. Involving employees in decision-making and in financial returns requires changes in training and other practices; this ensemble of human resource practices came to be known as the high-performance system. Some firms adopted only halfway measures, introducing employee involvement in decision-making but no incentives, or implementing financial incentives but no involvement in decision-making.[5]

The four systems can be differentiated along three principal dimensions: the organizational capabilities necessary for effective operation of a system, the costs of operating a system, and the benefits that stem from the operation of a system. Organizational capabilities, a concept emphasized by Chandler (1992), concerns a complex set of skills, know-how, and traditions that reside in many parts of an organization, in both management and workers, but cannot be observed directly. Organizational capabilities reflect the ability of managers to select the appropriate mechanisms for allocation of decision-making, the

[5] See Appelbaum and Batt (1994) and Cappelli et al. (1997) for historical accounts of the evolution of human resource systems.

appropriate incentives to induce employees and managers to act in the organization's interests and to put in place supporting practices such as training. An important element of organizational capabilities is the development and maintenance of organizational culture that promotes a sense of duty and dedication that mutes the effects of self-interest and ameliorates free ridership in ways that cannot be accomplished with incentives alone (Kreps, 1990, Kandel and Lazear, 1993, Ben-Ner and Jones, 1995). Organizational capabilities reside in managers and workers and their training or replacement may enhance organizational capabilities, but the fact that hiring is commonly done by existing staff various forces of inertia prevents significant transformation of a firm's capabilities. It is therefore meaningful to think of firms as having, in the short run, a nearly fixed level of organizational capabilities.[6]

In our framework, the costs required to operate effectively a particular human resources system are fixed and independent of organizational capabilities. The high-performance system is the most costly because it requires investment in training to enable employees to make sound decisions, and requires financial commitments to provide effective incentives. The decision-making and financial incentives systems each entails lower costs than the high-performance system; it is impossible to rank these systems without specific operational and contextual details. The lowest-cost system is the traditional system.[7] The magnitude of the benefits a firm can reap increases with organizational capabilities. Poor management can make a mess of a human resources system; for example, poorly-organized teams and expensive incentives that do not address appropriately free ridership can cause severe performance problems, and the more complex the system the more severe are the problems that poor management can cause. In contrast, a firm possessing superior organizational capabilities can take advantage of the potential of the high-performance system and can generate a higher level of performance than it could from employing any other system. Thus a high-capability firm performs best with the high-performance system, whereas a firm with low organizational capabilities performs best when it employs the traditional system. The intermediate systems yield greater benefits when supported by appropriate organizational capabilities, which rank in between the levels required by the traditional and high-performance systems. However, a decision-making system cannot operate effectively without the complement of financial incentives, that is, without being transformed into a high-performance system. The reason for that is that self-interested employees and management will use their decision-making power to pursue activities that benefit them rather than the organization. Similarly, a financial system may provide appropriate incentives but in the absence of decentralization of decision-making and delegation to employees, they cannot act on their incentives, which are therefore wasted. Thus, only the high-performance system can take advantage of the complementarity between financial incentives and decision-making delegation; an intermediate system will therefore perform worse than a high-performance system and possibly worse even than the traditional system (Ben-Ner and

[6] The near-constancy of rankings of academic departments bears witness to this idea.
[7] See Ichniowski and Shaw (1995) for a detailed discussion of the costs of operating different human resource systems. Note that these costs are on-going costs the firm pays for maintaining the system. We assume they are system-specific and time invariant.

Jones, 1995, Levine and Tyson, 1990). The question is therefore why would a firm adopt an intermediate system at all? The answer is probably that some firms cannot make the leap from the traditional to the high-performance system and move temporarily to an intermediate system. This is compatible with the two-stage transitions observed in Table 1.[8]

The foregoing argument emphasizes the contingency or match between capabilities and system,[9] and it can be formalized as follows. Define firm *j*'s productivity under system *s* at time *t* as [10]

$$y_{jts} = b_s\, x_{jt} - c_s + u_{jt}, \qquad (1)$$

where x_{jt} is firm *j*'s capabilities at time *t*, c_s and b_s are the costs and benefits of system *s*, respectively, and u_{jt} is a random productivity shock. For simplicity of exposition, assume that there are only two systems, H for high-performance and T for traditional.[11] The costs of implementing and operating the system that requires greater organizational capabilities, which we will term the more complex system, are larger than those associated with the traditional system: $c_H > c_T$. We further assume that the benefits from system H exceed those of system T, $b_H > b_T$ for all levels of organizational capabilities.

Figure 3 depicts productivity under systems H and T as a function of firm capabilities, assuming that managers know precisely their firms' capabilities as well as the costs and benefits of each system. Define $x^* = (c_H - c_T)/(b_H - b_T)$ as the level of capabilities that corresponds to equal productivity in both systems. Firms with capabilities $x_{jt} < x^*$ ($x_{jt} >= x^*$) have a comparative advantage in operating the traditional system, whereas firms with capabilities $x_{jt} >= x^*$ are more productive operating the high-performance system.

A firm's human resources system is adjusted over time as a result of learning by decision-makers. The three theories of learning differ with respect to the nature of the information that is learned and how it is learned. In learning-by-doing, firms learn how to do things better, that is, they improve their capabilities, x_{jt}. In matching theory, improved information about the firm's own capabilities leads to learning about the

[8] Gant, Ichniowski, and Shaw (2002) show that the process of transition from the traditional to the high-performance system entails not just the formal addition of incentives and the shifting of decision-making responsibilities to line employees, but also a complicated restructuring of a myriad of relationships among employees.

[9] Many researchers argue that the high-performance system generates better performance than other systems (e.g., Kochan and Osterman, 1994, MacDuffie 1995), but some authors claim that superior performance is contingent on organizational capabilities (Baron and Kreps, 1999).

[10] A similar productivity framework that integrates matching and learning has been used by Gibbons and Waldman (1999). In these authors' framework, learning about workers' ability affects the dynamics of switching to a higher or lower job level. An important assumption in their framework is that higher job levels are more sensitive to worker ability than lower job levels. In the present paper, we assume similarly that systems are rank-ordered by complexity level, and we assume that more complex systems bring greater benefits for higher-capability firms. The ordering of systems by complexity follows naturally from the definition of the traditional and high-performance systems. Although a ranking of the financial incentives and the decision-making systems is not obvious, both systems can be viewed as intermediary systems with complexity level in between the traditional and high-performance system. Although a distinction between the two systems would be necessary for generality of the analysis, the transition table (Table 1) shows that there are very few switches between the two systems.

[11] We conduct the discussion in this subsection in terms of these two systems only. The two intermediate systems, the decision-making system *D* and the financial incentives system *F*, are more complex than *T* but simpler than *H*. It is not possible, and it turns out that it is not necessary, to rank the two systems relative to each other because the limited number of observations forces us to treat the two systems in most analyses as the same. The analytical framework developed in this section can be readily extended to incorporate a third, intermediate system, and we do so in the estimation section.

match. In social learning theory, information about systems' costs and benefits is obtained from observing other firms operating these systems. We develop further these three theories and use them to understand how firms decide to keep or change systems.

a) Learning-by-doing

The economic literature on organizational learning can be traced to Arrow's (1962) contribution, which focused on the role of experience on organizational productivity; subsequent investigations examined the process of introduction, implementation, and assimilation of new production technologies. A key argument of this literature is that the mastery of a new technique by an organization requires adjustments and learning by many individuals who participate in production. This process takes time, and the initial productivity of a new technology will be only a fraction of its full potential. The theory predicts, and empirical findings generally support, the existence of a learning curve that implies that the productivity of a new technology rises over a few years, then levels off (Jovanovic and Nyarko, 1995, 1996, Cabral and Leiblein, 2001).

The learning-by-doing theory focuses on how experience enhances organizational capabilities. Let us assume that $x_{jt} = \gamma_j * t$, that is, capabilities are a function of experience t and a firm-specific capabilities parameter γ_j. This formulation allows for heterogeneity in the rate at which capabilities grow and for the possibility that higher-γ_j firms (those with greater baseline capabilities) learn faster than others. Learning from experience may improve an organization's ability to exploit more productively its current human resources system. At the same time, experience may also improve a firm's ability to operate *any* human resources system by generating knowledge that is transferable across systems. If organizational capabilities accumulate like human capital, then the longer a firm has experience with a relatively simple system, the better it will be able to take advantage of the greater productivity of a more complex system; therefore, as capabilities x_{jt} grow over time, at some point they reach the threshold level x^* for switching to the high-performance system H. Learning-by-doing therefore predicts that the length of experience with a particular system increases the likelihood of switching to a more complex system.[12]

Learning-by-doing also has implications for the dynamics of firm performance. In a "pure" learning-by-doing framework without firm heterogeneity, the typical learning curve predicts that after an initial period of adjustment to the new system, productivity will increase with experience (capabilities) but at a decreasing rate (Jovanovic and Nyarko, 1995). The introduction of firm heterogeneity implies that firms with different capabilities accumulate experience at different rates, leading to different learning curves. The difference in the productivity profiles of firms with the traditional and high-performance systems as a function of experience with each system is illustrated in Figure 4. For simplicity, we assume that there are

[12] This prediction depends on the extent to which the capabilities accumulated under one system are transferable to a more complex system. If there is no transferability at all, the length of experience should not affect the switching likelihood.

two types, low and high capability, γ_L and γ_H such that $\gamma_L < \gamma_H$, and following the optimal matching rule illustrated in Figure 3, γ_L (γ_H) firms are better matched with the traditional (high-performance) system. Therefore, in the presence of firm heterogeneity, an additional prediction of learning-by-doing is that the productivity profile of firms matched with the high-performance system should be above the profile of firms matched with the traditional system.

b) Learning about the match

We assume now that management does not observe perfectly the firm's organizational capabilities γ_j, but it does know the costs and benefits associated with each system. How do managers learn about their firms' capability to operate different human resource systems? The Bayesian learning literature, initiated by Jovanovic (1982), developed the idea that managers have some prior beliefs about their firms' organizational capabilities and update these beliefs using various signals they receive over time. The signal about capabilities is derived from equation (1): $Z_{jt} = \gamma_j*t + u_{jt} = (y_{jts} + c_s)/b_s$, where u_{jt} reflects productivity shocks. In this formulation, the signal, and therefore learning about γ_j, is independent of the firm's current system and is therefore extracted from the observation of the firm's productivity; with time-dependent productivity shocks, learning occurs gradually.[13]

Managers thus update their beliefs every period on the basis of the history of signals they extract from observing previous period productivity, $Z_0, \ldots, Z_m$, where m stands for the age of the firm.[14] The level of expected organizational capabilities therefore evolves over time as the beliefs change with changes in realized productivity. If the perceived capabilities exceed the threshold, management will decide to switch to a more complex system; otherwise it will stay with the current one. Higher realized productivity in one period resulting from a positive productivity shock u_{jt} signals to management that the firm may be of the high-capability type. It follows that the change in expected capabilities between t and $t+1$ is an increasing function of previous-period changes in productivity. The decision to switch to system H at time t will follow the realization of positive changes in productivity between $t-2$ and $t-1$, if the productivity increases are large enough to bring expected capabilities above the threshold for switching systems. The likelihood of switching to the more complex system is therefore positively associated with previous-period changes in productivity.[15]

In summary, the Bayesian learning framework suggests that the decision to move to a more complex human resources system should be positively influenced by past performance; more precisely, a recent *change* in performance supplies a signal that conveys new information about firm organizational capabilities. In assessing its capacity to embrace organizational innovations, management is likely not to

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[13] The Bayesian learning framework described here is an application of the framework defined in Gibbons and Waldman (1999).

[14] Defining $p = P(\gamma = \gamma_H / Z_{jt-m}, \ldots Z_{jt-1})$, the Bayes rule for updating beliefs is given by
$P(\gamma = \gamma_H / Z_{jt-m}, \ldots Z_{jt-1}, Z_{jt}) = [p*g(Z_{jt} - \gamma_H*t)]/[p*g(Z_{jt} - \gamma_H*t) + (1-p)*g(Z_{jt} - \gamma_H*t)]$, where g is the density of u_{jt}.

[15] See the Appendix in Gibbons and Waldman (1999) for a proof of this assertion.

rely on the firm's distant history of performance, but to seek new information in the form of *changes* in performance. Improvement in performance signals high organizational capabilities and therefore the suggestion to adopt a more costly but also more productive human resources system, whereas unchanged or declining performance indicates low capability and a suggestion to stay with the current system or possibly switch to a less complex system than the current one.

c) Social learning

Firms adjust their organizational structure not only by looking inward at their own experiences, but also by observing other firms' actions, as well as learning from consultants, colleagues in professional organizations, and academics. Just as individuals learn intentionally from other individuals (Merlo and Schotter, 2003), managers too may observe the behavior of other firms to learn effective ways of organizing their firms' human resources. Managers may also follow other firms' ways to gain legitimacy with employees, customers, suppliers, and others on whom they depend (Hannan and Freeman, 1978). Not all emulation is beneficial: managers may follow others in "herd behavior" fashion at the expense of more relevant signals, which is likely to result in inferior performance (Banerjee, 1992). Learning from the experience of others may complement or even substitute for learning from one's own experience.

If from their own experience managers learn how to do things better, or figure out their own capabilities, what may they learn from others' experiences? Other firms' experiences may supply information or signals about the costs and benefits of systems with which managers do not have direct experience. In particular, managers of firms with system T do not know precisely the costs and benefits of system H, and therefore do not know the minimum or threshold level of organizational capabilities x^* that a firm must possess in order to switch successfully to system H. Consider a manager in a firm with system T with prior beliefs about x^* represented by the distribution $g(x^*)$. The manager in firm j observes a signal $s_j = x^* + \varepsilon_j$, where ε_j is $N(0, \sigma^2_\varepsilon)$, and decides to switch to H if the firm's known organizational capabilities x_j exceed the signaled threshold capabilities, i.e., $x_j > s_j \equiv x^* + \varepsilon_j$. In a typical environment, the manager observes no more than the actual choices of other firms and needs to make sense of that information. The decisions of other firms (which have made their system selection decisions in the past) depend on their own capabilities as well as on their own beliefs about x^*. The manager reasons that all else equal, firms are more likely to adopt H if they receive a signal telling them that x^* is low because their capabilities are more likely to exceed a lower x^* than a higher one. Hence, the larger the number of adopters of H, the more likely that many firms received information that x^* is low. The manager incorporates this information into his or her own beliefs and revises downward the expectation of x^*.[16]

[16] Assume that in the previous period, there were N firms with system T that had to decide (irreversibly) whether to adopt H, based on no information other than their own signals. Each firm switches if and only if $x_j > s_j \equiv x^* + \varepsilon_j$. In the current period, from the point of view of the manager who seeks to make a decision whether to switch, the x_js and ε_js of the N firms are unobservable, and only the number of firms that chose to adopt the H system is known. The manager uses this information to make inferences about x^*. Let k be the number of firms observed to have

Managers can reduce the noise in the signals they observe by seeking information in addition to the proportion of firms using different systems. The information that managers seek and the value of what they learn from others may be correlated with their abilities: better managers are likely to more carefully seek out information relevant to their decisions. Managers will seek information not only regarding the distribution of systems but also about the performance of firms with different systems, with the obvious prediction that better-performing systems in a particular industry will be more likely to be adopted. Large firms enjoy economies of scale in taking on this sort of learning. Firms located near other firms are better placed for networking with colleagues and others who possess useful knowledge than are isolated firms (Jaffe, Trajtenberg, and Henderson, 1993, Beaudry and Breschi, 2003, Erickson and Jacoby, 2003). Firms located in or near large metropolitan areas usually have these advantages, as well as relatively easy access to sources of information about human resource systems—conferences, professional enhancement courses, consultants, academics, and higher-quality managers and employees—compared to firms located farther away (Audretsch and Lehman, 2005).[17]

In summary, the networking element of social learning suggests that learning is enhanced by geographic concentration of firms and proximity to centers of knowledge, particularly when many firms are in the same industry. The imitation aspect of social learning suggests that the larger the number of firms in an industry and geographic area that practice a particular system, the more likely that any individual firm will be exposed to information about that system and therefore adopt it; if managers can obtain information about the performance of firms with different systems, they will likely adopt the system that performs best in their industry. Overall, we expect that the quality and quantity of information firms obtain from observing others operating the more complex system will increase the likelihood of switching to that system.

d) Speed of learning

The speed with which a firm learns depends on how much decision-makers need to learn relative to their current knowledge, how fast they can learn, and how fast individual learning can be transformed into collective learning and action. Generally, these depend on the skills and knowledge of the individual decision-makers that populate them, the availability of resources they can use to aid learning, and how the organizational structure maps individual views into collective decisions.

The assumption that firms differ in their rate of growth of organizational capabilities ($x_{jt} = \gamma_j * t$) generates the prediction that firms with greater baseline capabilities will adopt more complex systems

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adopted H. Then the expected value of x* is a decreasing function of k. From the point of view of the manager, the probability that any one of the N firms adopts the more complex system H is given by $P_I(x^*) \equiv P(x_j - \varepsilon_j > x^*)$. Given x^* and N, the probability that exactly k out of N firms would choose system H is P(k |x*), which follows a binomial distribution (P(k |x*) = b(k |P$_I$(x*), N)). The manager makes inferences about x^* from k by applying Bayes' rule: $P(x^*|k) = P(k|x^*)\, P_I(x^*)/P(k) = b(k\,|P_I(x^*), N).\ g(x^*) /[\int b(k/ P_I(x^*), N).\ g(x^*)\, dx^*]$. Consider two different realizations of k, k_0 and k_1, where $k_0 < k_1$. The distribution $P(x^*|k_0)$ first-order stochastically dominates $P(x^*|k_1)$. The observation of a high realization of k causes the observing firm to update its beliefs about x^* by assigning more weight to the possibility that x^* is low and less weight to the possibility that x^* is high. The result is that $E(x^*|k) = \int p(x^*|k)\, x^*\, dx^*$ decreases in k. See Chamley and Gale (1994) for a more general framework.

[17] The location of firms in metropolitan areas is motivated in part by the desire to have access to knowledge and skilled employees (Glaeser and Maré, 2001).

faster. ‘Baseline capabilities’ is a concept that can be rarely observed and measured directly; however, it is often asserted that organizational capabilities are positively associated with firm size, location in a metropolitan area, and wages.[18]

Bureaucratic structures impede the transmission of knowledge through an organization and therefore organizational learning. Larger organizations are often more bureaucratic than smaller ones, but they also have access to more skilled employees and enjoy economies of scale in many areas, including the acquisition of information and learning.[19] Organizations located in large metropolitan areas have access to pools of skilled labor that are not available in other areas. They also have access to face-to-face networking opportunities. These factors contribute to faster learning. Because larger firms and firms in metropolitan areas are also high-wage firms, we expect that higher-wage firms will adopt new systems more rapidly (Bartel and Lichtenberg, 1987).

Organizational resistance may slow system change. Employees and managers may oppose change for material and psychological reasons. Moving away from a system of fixed wages (the traditional system or decision-making system) to one in which some compensation is at risk (the financial incentives system and the high-performance system) and from well-defined lines of responsibility (traditional system or financial incentives system) to greater employee involvement (decision-making and high-performance systems) represents threats to many employees and managers who are likely to oppose it. Hence, the longer an organization spends with a system, the greater the likelihood of resistance to change to another system. This factor operates in the same direction as learning-by-doing, adding to the negative effect of experience on changing to a more complex system. Firm age, which is correlated with experience, is similarly a deterrent on the speed of adoption. Older organizations have more long-established practices with employee interests tied to preserving them, so they are more likely to have internal obstacles to making changes associated with learning, and more obstacles to learning that may call for undesirable changes.

e) Summary of hypotheses

The discussion in this section focused on two systems, the traditional and the high-performance systems, the latter more complex than the former. We now summarize the discussion in the form of hypotheses and extend it to the four systems introduced earlier. As noted previously, the decision-making and financial systems are more complex than the traditional system but less so than the high-performance one, but we cannot rank them. We will treat the two intermediate systems as equally complex, and extend the predictions derived for the two systems to include the third intermediate possibility.

[18] It is well-known that larger firms pay higher wages and employ more skilled workers than smaller firms (Brown and Medoff, 1980, Troske, 1999). Florida (1995) argues that metropolitan areas attract more skilled workers; this relates to Glaeser and Maré’s (2001) argument about reasons for the location of firms.

[19] For example, many large organizations belong to professional organizations that are constituted primarily in order to exchange ideas and knowledge, have the ability to purchase the expertise of experts, and so on—things that small organizations cannot afford.

H1: Learning from experience by doing

The probability of switching to a more complex system increases with experience (H1a). Firm productivity increases with experience with a given system, but the rate of increase decreases over time (H1b). In the presence of firm heterogeneity and matching, the productivity profile of firms matched with the high-performance system should be above the productivity profile of firms matched with the less complex system (H1c).

H2: Learning about the match between a firm's abilities and its human resource system

The likelihood of switching to a more complex system increases with improvements in performance (H2).

H3: Social learning by observation

The likelihood of switching to a more complex system decreases with the degree of a firm's isolation from other firms (H3a) and increases with the proximity to a metropolitan center (H3b). The likelihood that a firm will switch to a particular system increases with the proportion of firms practicing that system (H3c) and with the average performance of similar firms that are already practicing that system (H3d).

H4: Speed of learning

The speed of adjustment to a more complex system increases with firm size (H4a), with firm average real wages (H4b), and with firm proximity to metropolitan centers (H4c) and decreases with firm age (H4d).

A firm may not know its own organizational capabilities and the costs and benefits of alternative human resource systems, and at the same time it may learn by doing from its own experience. Hence, the different approaches to learning do not necessarily compete with each other, but may be used in tandem or *seriatim* by a particular firm. The hypothesis testing in the next section allows explicitly for this possibility.

The conceptual framework we use has the advantage of combining different learning sources into a single productivity equation to derive predictions about learning outcomes in terms of human resource system and productivity changes. This perspective however does not address directly the role of complementary factors which also affect productivity and workplace organization changes, including computerization, production technology and business strategy (Bartel, Ichniowski and Shaw, 2005). In fact, our matching framework implicitly assumes that organizational capabilities γ_j is positively correlated with decisions of computerization and customized production (or that the benefits of the combination of computerization, customized production and high-performance system are greater for higher-capability firms); although we focus on how learning about γ_j affects firms' decisions related to workplace organization, learning about γ_j is also likely to affect the decision to complement the change in workplace organization with computerization and customized production strategies.[20]

III. Data and Variables

a) The dataset

Our main analysis focuses on 110 publicly-traded firms for which we assembled a longitudinal dataset. We obtained data on human resource practices, unionization status, geographic location, and other firm characteristics from the Minnesota Human Resources Management Practices Survey. Wage and employment data come from the Minnesota Department of Economic Security's unemployment insurance (UI) files, and financial data from Standard and Poor's Compustat. This section describes briefly the survey and the key variables.

The survey was administered in 1994 to all publicly-traded firms with at least 20 employees that were headquartered and operated in the state of Minnesota. The survey was conducted by mail, with a phone survey administered to the firms that did not respond. The overall response rate was 61% (177 firms), a rate that exceeds that of most similar surveys. The sample period was determined primarily by the availability of wage and employment data from 1980 on. The panel dataset spans the period 1980–1994 and consists of time-variant and a few time-invariant variables. The final sample consists of up to 110 firms for which the key financial variables were available from Compustat as well as information on firm size and industry.[21] The variables used in the analysis are summarized in Appendix Table A1. In addition to the data for the publicly-traded firms, we have longitudinal data – but no financial information – for 690 privately-held firms; the data for these firms come from the same sources as for the publicly-traded firms. For coherence and completeness of analysis, we focus our attention on the sample of publicly-traded firms for which we have information on performance outcome, but for comparison purposes we present results for the full sample of firms in Appendix Table 2. The sample is unbalanced in that not all firms are observed over the same period; for the sample of publicly-traded firms, the number of firms at the start of the sample period was 39, and by the year of the survey (1994), the number was 110. Overall, the average number of years a firm is in the sample is 7.8 years.

[20] Validating empirically this claim requires longitudinal information on computerization, production technologies and business strategy decisions in addition to the firm's choice of human resource system. Unfortunately we do not have this information in our dataset. On the other hand, the survey provides information on the task environment within firms for the core employees for the survey year of 1994 and in particular, the level of complexity of the tasks performed. We do find a strong significant positive effect of task complexity on the likelihood of choosing a more complex system after running either a multinomial logit for the likelihood of choosing the traditional, intermediate or high-performance systems or an ordered logit (controlling for firm characteristics such as industry, unionization and firm size). This is consistent with the idea of a positive correlation between technology and workplace organization.

[21] Because the analysis hereafter requires the use of lags in performance changes, the final sample contains 110 firms with at least 2 years of data on all the variables and the sample period reduces to 13 years, from 1982-1994.

Responding firms provided detailed current information about various human resource practices and other facets of their internal organization, including the year the practices were introduced or discontinued.[22] We constructed the dummy variables that represent the four human resource systems, the key dependent variables in this paper, as follows. The variable that represents the system that entails employee involvement in decision-making (D) is coded 1 in year *t* if the firm had at least one of the following employee involvement programs in that year: quality of working life teams, quality circles, autonomous work teams, joint labor-management teams, or employee representatives on the board of directors. The variable that represents the financial incentives system (F) is coded 1 if the firm had at least one of the following: an employee stock ownership or purchase plan, a current or deferred profit-sharing plan, a gain-sharing plan, or a group bonus plan. The high-performance system (H) was coded 1 if the firm had both F=1 and D=1, whereas the traditional system (T) was coded 1 if the firm had both F=0 and D=0.

In terms of system changes, 72.7% of firms (80 out of 110 firms) experience at least one system switch. Table 1 provides the number of potential and actual transitions across systems (where the unit of observation is firm-year). As noted in the Introduction, about 90% of the potential transitions entailed a decision to stay with the current system. Most of the actual transitions represent switching from the traditional system to the financial incentives, decision-making, and high-performance systems, followed by switches from the financial incentives system to the high-performance system. The high-performance system is the most stable one, with only five moves out of it, none of which are to the traditional system.

b) Variables

Multiple variables were used to characterize the different learning mechanism. For *learning-by-doing*, we use information on the number of years of experience with a system (including experience prior to 1980, as this variable does not require wage or employment information). The system with which firms have most experience is, of course, the traditional system. The high-performance system, being the most recent, has been in use for only 1.52 years on average. For *matching*, we use the lagged difference in relative returns on investment (ROI). To compute the relative returns, average returns on investment in the firm's industry were subtracted from the firm's own returns on investment. Industry categories are broadly defined as services, trade, and manufacturing.

For *social learning*, we characterize variables associated with geographic concentration using information on the firm's total distance to other firms as a measure of the firm's isolation and its

[22] The survey is available at http://webpages.csom.umn.edu/hrir/abenner/web/papers/work-surv/work-surv-01.pdf. Respondents were typically the highest human resources executive in the firm; in smaller firms the respondent was frequently the top executive in the firm. We debriefed several respondents about how they obtained retrospective information about dates of introduction and discontinuation of practices; we were told that it came mostly from company records or their or their colleagues' recollections.

networking opportunities.[23] To capture opportunities for learning from other sources as well as for networking, we use a firm's distance to downtown Minneapolis. We chose downtown Minneapolis because several important institutions that provide opportunities for networking or transfer of knowledge are located there.[24] The distance measures were computed based on information on a firm's postal zip code, using the software package Zip Code Distance Wizard.[25] We characterize information about other firms' systems by computing the distribution of systems in the firm's own industry as well as the average performance of firms in the firm's own industry under each system. Because firms may use information about other firms more similar to them in other aspects in addition to industry, these two measures were also computed using system and performance information for firms with similar size, age, and similarly located within 10 miles of Minneapolis.[26]

In addition to the previous variables, we use firm size, the firm's industry (manufacturing, trade, or services) and whether the firm's workforce is unionized as control variables. We also use information about the firm's average real wages to control for firm heterogeneity. Due to a potential endogeneity problem, we use information about the firm's average real wages only in the year the firm entered the sample. Sample statistics for these variables are presented in Appendix Table 1 (for time-variant variables, the means are calculated over time).

In the analysis of the speed of learning, we concentrate on the effects of firm age and size, the distance measures discussed previously, and average real wage when a firm entered the sample, as well as a firm's industry and unionization status.

IV. Empirical Strategy

Learning is not observable; we can only identify the consequences of learning, which in the present analysis correspond to the presence or absence of system change at a given point in time as well as to improvement in performance. Our estimation strategy regarding system change is based on a latent variable framework in which the latent variable represents the year-to-year net benefits of system adjustments. We make inferences about the net benefits associated with a system change from the observation of a firm's decision whether to change its system in a given year. Learning is captured empirically through variables that reflect the extent of a firm's knowledge of the current and other available systems as well as of its own capabilities to operate the systems. In the learning-by-doing framework, learning about the system's

[23] The total distance from other firms reflects only firms in our dataset. This may not be fully representative of the actual distribution of firms across the state and therefore of the true networking opportunities each firm faces. The variable indicating total distance from other firms is therefore likely to be a biased measure of the extent of firms' isolation.
[24] For example, the University of Minnesota's Technology Transfer Office and School of Management are within a mile of the center point, as is the meeting place of the human resource executives' organization mentioned in footnote 3. We experimented with broadening the center point, but the results are essentially unchanged.
[25] The software is sold by Atlantic Coast PLC, located in Devon, England.
[26] We used three categories for firm size (less than 99 employees, 100–499 employees, and 500 or more employees) and four categories for firm age (less than 4 years, 5–10 years, 11–20 years, and above 20 years).

specificities is reflected in a firm's accumulated capabilities to run its current system; these capabilities are assumed to be perfectly observed. The matching and social learning frameworks introduce imperfect information, and learning consists of firms' usage of signals to make inferences about imperfectly observable variables, their own organizational capabilities, and the systems' costs and benefits. In addition, we estimate productivity profiles as a function of system experience to test for the existence of a learning curve.

To assess empirically the importance of the three learning mechanisms for a firm's decision to adjust its system of human resources and the speed of adjustment, we employ estimation strategies based on logit and multinomial estimations, and conduct hazard estimations of the likelihood of system adjustment. Our objective is to test for the presence of significant learning effects on system adjustments (following the hypotheses summarized at the end of section II) against the null of no significant learning effects for each of the learning variables we have identified. For matching and social learning, the insignificance of variables that stand for the various signals (change in performance, distance to other firms, etc.) would imply no learning associated with these particular variables. However, in the context of learning-by-doing, successful learning may lead managers to the conclusion that a system adjustment should not occur, just as would absence of learning. Our empirical question is therefore not about whether firms learn, but rather to assess what firms learn when making decisions to change systems. The finding of significant learning effects on firms' adjustments decisions provides evidence against effects associated with random occurrences and luck.

We interpret the significance of the variables described above as evidence of learning effects on the likelihood of switching systems but alternative explanations that do not necessarily involve learning may be proposed. For example, experience with a system may proxy for other factors we cannot measure with our data like timing issues related to the implementation of computerization or a change in business strategy which are complementary to the adoption of a more complex human resources system. Whereas we assume that a positive change in performance reflects greater (unmeasured) firm capabilities, this may also reflect greater availability of resources that permit implementation of more complex systems. We assume that access to knowledge through proximity to a city positively influences the switch to a more complex system, but it is possible that more innovative firms locate near cities (so that geographic location is not exogenous as we assume) and innovative firms are also more likely to adopt more complex human resource systems. These explanations notwithstanding, our results provide evidence of the informational role of the included variables, which we interpret as proxies for learning.

The three approaches to learning describe learning mechanisms that many firms are likely to use concurrently. An estimation framework of a firm's decision to adjust or keep a system that combines or nests the three mechanisms may be written as follows:

$$P(S_t/S'_{t-1}) = F_1(exp_{ts}) + F_2(\Delta y_{jt-1}) + F_3(I_{Nothers\ at\ t-1}, I_{Pothers\ at\ t-1}, log(1+ Dist_{city})) + \varepsilon_t\ , \qquad (2)$$

where S_t is the new system and S'_{t-1} is the previous system, F_1 is the learning-by-doing effect described by a function of experience with a given system at time t, F_2 is the matching effect, a function of previous changes in firm performance, and F_3 is the social learning function based on previous-period information about the distribution of firms and their average performance by system ($I_{Nothers}$ and $I_{Pothers}$),[27] the sum of the distance of the firm to Minneapolis[28], and ε_t is a random noise.

We implemented this general framework in two ways, balancing generality with data restrictions. We first estimated the likelihood of a *change to a more complex human resources system* (from T to F, D, or H, or from F and D to H) versus the alternative of *no change in system or change to a less complex system*, against the variables listed in equation (2).[29] In this logit estimation, the probabilities of adjusting systems are independent of a firm's current system.

Next we further investigate the different learning effects by estimating separate conditional probability frameworks by the type of a firm's current system.[30] We perform multinomial estimations of the likelihood of switching out of the traditional system either into the decision-making or financial incentives system, and logit estimations for the likelihood of switching out of the decision-making or financial incentive systems into the high-performance system.[31]

In addition, we investigate the speed of learning by estimating a hazard model of factors that may affect the timing of adoption of a more complex system; we estimate a Cox proportional hazard model and parametric hazard models based on the exponential and Weibull distributions.

Finally, for evidence of a learning curve implied by learning-by-doing, we estimate and test for the concavity of productivity profiles as a function of experience with a given system; we regress firm performance as measured by the firm's returns on investment (ROI) on a quadratic function of system experience, controlling for industry, union, and firm size.[32] Moreover, the presence of firm heterogeneity and matching effects on the learning curve can be emphasized indirectly by comparing differences in the

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27 $INothers = \frac{\sum_S N_j^{S(t-1)}}{N_j^{(t-1)}}$, $IPothers = \frac{\sum_S y_j^{S(t-1)}}{N_j^{(t-1)}}$, where N is the number of firms at $t-1$, y is firm productivity, j indexes the industry, and s indexes the human resources system of firms in industry j at $t-1$.

28 We also used $Dist_{others}$, the sum of the distances of the firm to other firms as well as $Dist_{SysH}$, the sum of the distances of the firm to other firms with the high-performance system.

29 As Table 1 indicates, very few changes are made to a lower-complexity system, so these cannot be evaluated separately.

30 Learning effects may depend on a firm's current system, and the learning mechanism on which a firm relies more may also be a function of its current system. For example, firms with the traditional system may learn more from their own experience than firms that have already adopted a somewhat complex system like the financial incentive or decision-making systems, and learning about a firm's own capabilities may be more important for the decision to switch out of the traditional system than learning about costs and benefits of a system by observing other firms' information.

31 A multinomial estimation is not possible in this case because of the small number of transitions out of systems D or F down to system T.

32 The quadratic function seems to be a natural choice for estimating productivity profiles but may also be too restrictive. To add more flexibility, we also performed the estimations adding a cubic term to the specification.

profiles of firm performance across systems.[33] To take into account the compositional bias in the estimation of the yearly performance profile for a given system caused by the presence of firms joining in or switching out of that system at any point in time, we perform the estimations only on the sample of firms that did not experience a change in system over the 13-year sample period, for which we assume that matching may have occurred in the past. We also include observations post-change for firms that indicate a change in system in a given year during the sample period. The significance of the quadratic term provides evidence in favor of the concavity of the learning curve, and significant differences in the slopes of the profiles across systems would indicate the importance of matching effects.

V. Results

The presentation of the results follows the order suggested by the empirical strategy. The logit analysis is reported in Table 2. The results of the separate probability estimations by type of system for each learning mechanism are given in Tables 3, 4, and 5. The results from the hazard analysis are in Table 6. The results of the performance regressions are presented in Table 7 and illustrated in Figure 5. Appendix A provides a discussion of the sample size differences associated with the use of different dependent variables in different analyses.

a) Learning-by-Doing, Matching, and Social Learning

Column (1) of Table 2 focuses on learning-by-doing, column (2) on matching, and columns (3)–(6) summarize the social learning results. The last two columns present the results when the three learning mechanisms are estimated jointly with different social learning measures. The results in column (1) show that the marginal effect of experience with a given system is to reduce the likelihood of switching to a more complex system with a negative estimated slope and positive quadratic term. The effect is significant for the financial incentives system. The effect for the decision-making system is similar but more imprecisely estimated and the effect for the traditional system is weaker. The U-shape pattern implies that experience with a given system starts to have a positive effect on the likelihood of switching after a few years. In particular, one can compute that it takes 12 years of accumulated experience for experience with the traditional system to increase the likelihood of switching to a more complex system, while it takes only 5.9 years for experience with the financial incentives system and three years for experience with the decision-making system to increase the probability of a system switch. It therefore takes a while for a firm to accumulate expertise that enables it to operate a more complex system. The time required to develop such

[33] To emphasize the combined effects of learning-by-doing and matching, productivity profiles could be estimated based on equation (1). The presence of endogeneity in the choice of workplace system and in the decision to switch system (due to learning) implies the use of nonlinear instrumental variable estimation in the same spirit as Gibbons, Katz, Lemieux and Parent (2005) and Lluis (2005). However the small size of our sample limits our ability to use such a procedure.

expertise depends on a firm's current system: it takes longer to be ready to switch out of the traditional system than from the decision-making or financial incentives systems. In terms of our initial hypotheses, these results imply that hypothesis (H1a) is supported weakly for the decision-making and traditional systems, and is supported strongly for the financial incentives system.

The result in column (2) is consistent with learning about the match between organizational capabilities and system requirements. Previous-period changes in performance increase the likelihood of switching to a more complex system; past improvements in the firm's performance seem to be a good predictor of the firm's capabilities and therefore of the decision to adopt a more complex and better-performing system.

The estimates on social learning variables suggest that this mechanism has some influence on firms' decisions to adjust their human resource systems. Greater distance from the state's main metropolitan center (Minneapolis) as well as greater distance from other firms (a measure of a firm's degree of isolation) both reduce the likelihood of switching to a more complex system (columns 3 and 4), in line with hypothesis H3a, albeit at marginal statistical significance levels.[34] Information about the distribution of the four systems in general as well as in cells with similar industry, age, size, and location has no significant effect on a firm's likelihood of switching to a more complex system. Information about firms' average performance under the high-performance system increases the likelihood of adopting a more complex system, as predicted by hypothesis H3b. However, information about the financial incentives system's performance contradicts this hypothesis, as does (more weakly) information about the decision-making and traditional systems. Thus, social learning seems to operate most significantly through favorable information about the performance effects of the high-performance system, and the better-located firms seem to learn to switch to a more complex system more often than their counterparts in faraway places.

The last two columns of Table 2 examine jointly the three learning mechanisms. Column (7) corresponds to social learning variables as specified in column (5), and column (8) corresponds to the specification of column (6); for space reasons, we show the results with only one distance variable (to Minneapolis).[35] The combination of all the variables associated with the three learning mechanisms does not reduce their individual effects (except for the distance variable). This suggests that the mechanisms have complementary roles in explaining firms' decisions to switch to a more complex system.

These results are based on the sample of publicly-traded firms, and the results might not generalize to privately-held firms. To investigate this possibility, we replicated the logit estimations from the analysis in Table 2 for the full sample including privately-held firms. The results are presented in Appendix Table A2. We find that the learning effects we could estimate (learning-by-doing and social learning, since matching involves the use of the financial performance measure ROI), are similar in terms of the sign of the

[34] The results associated with the total distance from other firms in column (4) should be indicative only of the effect of a firm's isolation on system switching. As mentioned in section II.b and footnote 23, this variable is a weak measure of a firm's isolation from other firms.
[35] The other distance variable's effects were similar to those estimated in columns (3) and (4) with slightly weaker significance levels.

estimated coefficients. The effects, however, are of smaller magnitude. We also find that the dummy variable indicating whether the firm is publicly traded has a positive and significant effect on the likelihood of switching to a more complex system. A comparison of average characteristics for the full sample and the sample of publicly-traded firms shows that privately-held firms are on average older and smaller, as well as located farther away from Minneapolis (see appendix Table A1). These results suggest that privately-held firms tend to be more traditional and conservative; they may be less prone to adjustments in their human resources system and therefore less sensitive to learning opportunities.

b) Learning Mechanisms by Current System

Tables 3, 4, and 5 present the results for learning-by-doing, matching, and social learning, respectively. The left panel of each table shows the results of the multinomial analysis for firms with the traditional system considering the decision to stay with it or to switch to the decision-making or financial incentives system, or to the high-performance system. The right panel shows the results of the logit analysis for the decision to stay with or to switch from the decision-making and financial incentives systems into the high-performance system.[36]

Table 3 indicates that there is no significant effect of experience with the traditional system[37] on the likelihood of switching out of it, neither to the decision-making or financial incentive systems nor to the high-performance system. Consistent with results in Table 2, hypothesis (H1a) is not supported for the traditional system. For firms that have already the decision-making or financial incentives system, the likelihood of switching to the high-performance system (right panel) is affected significantly by experience with each system, with weaker effects for the traditional system and stronger effects for the decision-making and financial incentives systems. Similar to the results in Table 2, it takes longer (12.5 years) for experience with the traditional system to increase the probability of a switch to the high-performance system and less for the decision-making and financial incentive systems (2.5 and 3.04 respectively). Hypothesis (H1a) is thus strongly supported for experience with the decision-making and financial incentive systems.

Table 4 investigates the matching mechanism. The left panel indicates that past changes in performance have no significant effect on the decision to switch out of the traditional system, whereas the right panel shows that an increase in past performance affects significantly the decision to switch out of the decision-making and financial incentives systems into the high-performance system. These results suggest that improvements in past performance serve as a signal of greater capabilities only to firms that have

[36] As noted earlier, switches to and from D and F were combined because we do not have information about their relative complexity and because the number of observations in each is too small for statistical analysis. There is only one transition from D or F to T, and we combined that observation with the observations reflecting no changes in system.

[37] With one exception, all the firms with the traditional system have always had that system, so for those firms, experience with the system corresponds to their age. These firms did not have experience with other systems, so the left panel presents estimates only on age *cum* experience with the traditional system.

already implemented an intermediate system. The matching results in Tables 4 and 2 are not robust to the inclusion of average real wage in the estimations. If average real wage proxies for firm-specific heterogeneity, it may capture variations in the capability parameter γ_j. As a result of its inclusion, there may be no more variation left to be explained by past performance changes that are also assumed to reflect firm capabilities. Hence our finding that changes in performance signal to management its firm's capabilities seems to hold.

Table 5 analyzes the effects of social learning variables. The variables associated with distance to Minneapolis, total distance from other firms, and total distance from firms with the high-performance system have a positive and significant impact on the likelihood of switching out of the traditional system into the decision-making and financial incentives systems but not to the high-performance system (columns 1–3). Interestingly, they increase the likelihood of adopting the decision-making and financial incentives systems. This suggests the possibility that distance away from sources of information about how to use the high-performance system leads firms to be more cautious and to make adjustments in stages, moving first to an intermediate system and only later to the full high-performance system.[38]

The distribution of systems in a firm's own industry (column 4) does not have a statistically significant effect on the decision to switch from the traditional system to either the decision-making or financial incentives systems or to the high-performance system. However, the performance of firms in a firm's own industry does have an effect on the switch from the traditional to high-performance system but not to the intermediate systems. Specifically, the better the average performance of firms using the high-performance system, the greater the likelihood of switching to the high-performance system, whereas the average performance of firms using the financial incentives system reduces the firm's likelihood of switching to the high-performance system. These results imply that firms with the traditional system tend to react to the performance of firms with the financial incentives and high-performance systems and switch to these systems when performance is favorable. There is no similar effect from the performance of firms with the decision-making system, probably because at any point in time, few such firms are in any given firm's environment, as they constitute less than 10% of the sample and probably of all firms, whereas the financial incentives and high-performance firms represent more than half the firms for much of the period under consideration. A more detailed look at the data, including information about the firm's location, age, size, and industry, as we have done in column (6) of Table 2, was not feasible here (recall that we are controlling here for the firm's current system).

Firms with the intermediate systems (the right panel in Table 5) do not seem to be influenced in their decisions by distance variables, perhaps because the influence of these variables was already exercised

[38] The absence of significance for the decision to adopt the full system may also be the result of the small number of transitions from T to H (there are just six switches from the traditional system directly into the high-performance system).

in the switch from the traditional system to the current system. However, a sizeable effect is measured on the performance of firms with the high-performance system, albeit without a lot of precision.

In summary, the findings of Tables 3, 4, and 5 suggest that learning-by-doing plays a significant role in the decision to switch out of both the traditional system and the decision-making and financial incentives systems, whereas matching and social learning effects are more or less important depending upon which system currently in use. In particular, when it comes to deciding whether to switch to the high-performance system, firms using the decision-making or financial incentive systems seem to put more weight on their own signal about expected capabilities than on information from others. When deciding whether to adopt a more complex system, however, firms using the traditional system seem to be influenced more by social learning measures.

c) Speed of Learning

In order to identify potential determinants of firms' speed of learning, we estimated hazard models for the time to switch to the high-performance system, and to the decision-making or financial incentives systems.[39] While we previously estimated the importance of specific learning-related variables on the likelihood of system adjustments in Tables 2–5, our objective in the following analysis is to estimate the effect of particular firm characteristics on the timing of these adjustments. The results are presented in Table 6. The comparison of the hazard models based on the log likelihood suggests that the exponential and Weibull models might fit better the data. The AIC criterion suggests that the Weibull model is preferred over the exponential model.

The results for the switch to the high-performance system (left panel) show that the firm's birth year negatively affects the hazard, suggesting that younger firms are more likely to adopt sooner than older firms. Larger firms and higher-wage firms (firms with higher average real wages when they entered the sample) are faster adopters of the high-performance system. Distance from Minneapolis has no significant effect on the hazard of adoption of the high-performance system.

The analysis of the hazard of switching to the decision-making or financial incentives systems (right panel) shows similar results for the negative effect of age on the conditional probability of adopting the intermediate system. Interestingly, greater distance to Minneapolis increases the hazard into the intermediate system, whereas firm size is only weakly significant and not significant under the exponential and Weibull hazard models.

Overall, the hazard analysis suggests that younger firms are faster adopters of both the high-performance and the intermediate systems. This result is consistent with the previous analysis showing that firms with more experience with the traditional system are less likely to adopt a more complex system, potentially because of employee resistance or because organizational capabilities necessary to operate more

[39] A competing hazards model taking into account all the transitions could not be used due to the small number of observations.

complex practices are orthogonal to those learned from accumulated experience under the traditional system. This is consistent with the findings in Tables 2 and 3. As expected, larger firms and high-wage firms are more likely to be early adopters of the high-performance system. Consistent with the social learning findings in Table 5, firms farther away from the metropolitan center are more likely to adopt the intermediate systems instead of the full high-performance system.

d) Learning Curve

Table 7 presents the results of OLS estimations of performance measured as the firm's returns on investment as a quadratic function of a firm's years of experience. These analyses are conducted for the sample of firms that did not experience a change in system, and for observations following the change to a new system for those firms that did switch systems.[40] The resulting learning curves—predicted profiles using these estimates—are illustrated in Figure 5. The coefficients associated with experience with the traditional system are not significant, and the learning curve is, of course, flat. The slope coefficients for the high-performance profile are significant at the 5% level, and their sign is consistent with a concave learning curve as stated in hypothesis (H1b). The coefficients associated with the performance profile of the financial incentives system are also significant at the 5% level but not in the expected direction. The predicted performance profile is convex with an original decrease in performance and an increase after about 11 years of accumulated experience. This conforms with our hypothesis that, in contrast to the high-performance system, this system is unbalanced and firms that adopt it find it difficult to make it work, causing a fall in performance with very slow recovery. The comparison of the performance profiles across systems also emphasizes the importance of the matching effect, as the high-performance profile stands above the others (hypothesis H1c).

e) Summary of Empirical Results Relative to Theoretical Hypotheses

We find evidence in favor of hypothesis (H1a) that learning-by-doing increases the likelihood of switching to the high-performance system for the decision-making and financial incentive systems after a minimum of accumulated experience, but not so for the traditional system. We find strong evidence of learning-by-doing effects for firms in the high-performance system, consistent with the learning curve hypothesized in (H1b); we do not find evidence of learning from experience for the traditional system, and for the financial system we find that the adoption of a new system is associated with a decline in productivity. The latter finding suggests that organizational capabilities honed in predecessor systems (mostly the traditional one) do not help with running the financial incentives system. This is also consistent with hypothesis (H1a) in that accumulated experience with the financial incentives system increases not

[40] For the decision-making system there are no observations of non-changers and there are very few observations of changers, so system D was not included in this analysis. The results of the analysis with a cubic function of experience are not shown, as the cubic terms were not significant.

only organizational capabilities but also the need to switch to a more balanced human resources system. The results are also indicative of the importance of matching effects as stated in hypothesis (H1c).

We find evidence that improvements in performance influence a firm's decision to change to a more complex system, consistent with the matching hypothesis (H2). For social learning, we find some evidence for hypothesis (H3a) concerning the effects on learning associated with a firm's isolation and find stronger evidence for hypothesis (H3b) for the impact of the distance to the metropolitan center. There is some support for (H3c) and (H3d) related to the role of information on firms' distribution by system and performance within the firm's own industry; the results are weaker when we use measures based on information for firms similar in size, age, and location to the firm under analysis, but this may be due to the sensitivity of these measures to the categorization used and the definition of the cells.

The hypotheses regarding the effect of firm size (positive), firm age (negative), and average wage (positive) on the speed of learning are supported. The hypothesis regarding the effect of location (H4c) is rejected: distance to the metropolitan center does not hasten adoption of the high-performance system, and it is associated with longer time to adoption of the intermediate systems.

VI. Conclusions

In this paper we examined how firms adjust their human resource systems by investigating what information they appear to use in their decision-making. Managers have incomplete information about important organizational matters regarding organization structure in general and human resource systems in particular: they don't know their firms' precise organizational capabilities, they cannot discern precisely the role of such capabilities versus the market in determining firm financial performance, and they don't know exactly how other firms are organized and what effect their human resource systems have on performance. When they come to make decisions about organizational matters, managers may rely on what they learn from various sources: (1) the knowledge derived from experience with certain human resource systems, which may allow their firm to either improve performance with the current system or to switch to a more complex and better-performing system (the *learning-by-doing mechanism*), (2) observation of their firm's past performance to understand better its capabilities and assess whether these match the needs of a more complex system than the one they already possess (the *matching mechanism*), and (3) information obtained from other sources such as peers and consultants, as well as data about other firms' behavior and performance (the *social learning mechanism*).

Drawing on a unique dataset, this paper has thrown light on the three learning mechanisms by examining annual decisions that individual firms made over time regarding their human resources system. Firms chose to stay with their current human resources system about 90% of the time, whereas the adjustments they did make entailed almost always a switch to a more complex system: from the traditional system to an intermediate system (financial incentives or decision-making) or (much less frequently) to the high-performance system, or from an intermediate system to the high-performance system. Of course, we do not know what information managers actually had at their disposal or used in making their decisions. Asking managers who respond to a survey to supply answers about information they or their predecessors had when they made the decisions cannot bring out meaningful answers. Instead, we employed the standard approach of inferring about the determinants of learning from the degree to which these determinants appear to have influenced the object of learning, the choice of human resource systems.

A sizable literature has investigated the three learning mechanisms in a variety of contexts, often concerning the adoption of technology. But this appears to be the first paper to evaluate simultaneously the here mechanisms. Perhaps not surprisingly, we found that organizational learning in the context of human resource systems is multifaceted and that firms rely on multiple sources of information to make their decisions: learning-by-doing, learning about the match, and social learning all play significant roles in explaining a firm's likelihood of switching to a more complex system.

The accumulation of experience with a given system, i.e., learning by doing, has a twofold effect. Initially it entrenches the system, particularly the traditional one, by enhancing a firm's ability to extract value from it. After several years, experience with a system, especially the intermediate ones, improves firms' ability to operate the high-performance system; experience also seems to make firms aware of the deficiencies of relying on an unbalanced system and of the advantage of switching to the high-performance system to take advantage of the complementarity be financial incentives and decentralized decision-making.[41] These conclusions are supported by the estimated learning curves, which replicate the classic learning curve only for the most complex (high-performance) system, but not the other systems. The theory that firms learn about their organizational capabilities and assess them relative to the requirements associated with more complex systems is supported by the finding that recent improvements in a firm's financial performance relative to its industry provides a signal to managers that their firm's organizational capabilities are suitable for switching to a more complex system and therefore for taking advantage of its better performance. This result supports a major tenet of Bayesian learning theory and suggests that managers seem to carefully watch their firm's performance for possibilities to exploit productive advantages. Social learning, as reflected in the use of information about the distribution and performance of human resource systems among other firms and proximity to the state's metropolitan center, is an important factor in firms' decision to switch to a more complex system.

Firms thus behave as if they use both private and public information as well as networking opportunities to make decisions about adjustments in their human resource systems. Which source of information firms use (their own versus others') seems to depend on their current system. Interestingly, information about a firm's own performance matters most for switching out of the intermediate systems to

[41] Cabral and Leiblein (2001) find that experience with an old semiconductor technology negatively affects the adoption of a new technology but their specification does not consider the possibility of a quadratic function of experience. If we analyze experience linearly, we also find significant negative effects of experience with simpler systems on the likelihood of switching to a more complex system. Results are available upon request.

the high-performance system, whereas information about other firms is more relevant to firms when they consider switching out of the traditional system. Our findings are consistent with the possibility that the switch from the traditional system into the intermediate systems is often part of a planned subsequent switch to the high-performance system. The switch into the intermediate systems of decision-making and financial incentives is explained primarily by firms' geographic location: the closer firms with the traditional system are to other firms, to the metropolitan center, or to firms that have the high-performance system, the more likely they are to switch. This suggests that social learning about more complex systems is important in managers' decision-making, with some weight attached to their firm's recent performance. However, the switch from the intermediate systems to the high-performance system is based on experience with the current system and on performance signals, on the firm's recent improvements, and on the average performance of firms that already have the high-performance system. This two-stage progression of human resource systems reveals a fairly cautious and sophisticated learning process, for it seems to reveal use of different information sets at different decision junctures. The initial decision to switch out of the traditional system is based on social learning, primarily through networks of local knowledge in firms and other institutions, with some positive signals about organizational capabilities, whereas the second and final switch is based on the receipt of further positive information about a firm's own organizational capabilities, as well as about recent favorable performance of the high-performance system. The transition from one system to another is carried out at different speeds by different firms. The firms that switch faster to a more complex system are larger, younger, and located closer to the metropolitan center.

The geographic location of a firm is an important determinant of its learning. In our single-state sample, proximity to the metropolitan center that houses the state's research university, consulting firms, and other institutions that generate and transmit knowledge contributes substantially to a firm's likelihood to adopt more complex human resource systems, and to do so faster. The idea of knowledge passing through local networks has support in the literature in various contexts. As Florida (1995) put it, "Learning regions function as collectors and repositories of knowledge and ideas, and provide the underlying environment or infrastructure which facilitates the flow of knowledge, ideas and learning." Krugman (1991) identified metropolitan areas as centers of specialized knowledge and places where knowledge can be transmitted among firms. Other economists found that learning in diverse contexts is affected by geography. Jaffe, Trajtenberg, and Henderson (1993) found that geography is important for citation of patents, despite the fact that the patents are in the public domain and available for anyone anywhere to read: the citation rate is an inverse function of distance from the location where the patent was discovered. Even in the era of fast and essentially costless transmission of information, sophisticated financial traders (whose stakes are high) seem to rely more heavily on local word of mouth than on other forms of learning about what stocks to trade (Hong, Kubik and Stein, 2005). A fascinating question is why geography is seemingly such an important component of learning. Whereas sociologists have long considered social networks and the locations to which these networks are tied very important for understanding social phenomena (Smith-Doerr and Powell, 2005), only recently have economists come to incorporate these concepts in economic analysis. Examination of social learning and the question of whether it is, for certain purposes, more efficient than other learning mechanisms may be a fruitful undertaking with important business and policy implications.

A further natural extension of this paper's analysis of learning effects on decision adoption would be to estimate the comparative benefits of different learning mechanisms in terms of performance. Although the small size of our sample makes it difficult to adequately estimate productivity profiles combining learning-by-doing and matching effects as in equation (1), we can compare performance outcomes of firms before and after a change of system as well as performance outcomes of system "changers" versus "non-changers" over the sample period. An analysis of the experience-performance profiles (using return on investment) for different subsamples of observations suggests that firms that remained under the traditional system throughout the period have flatter experience-performance profiles than do firms that remained with the high-performance system. If there is a similar learning curve across systems and firms, then this result suggests that traditional firms would stand on the flat part of the curve while the high-performance system adopters would be on the steeper part. Matching effects may also imply that these results are due to the fact that more efficient firms are also the ones that keep the high-performance system. Future research should emphasize the performance dynamics of firms following different system adjustment paths.

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Figure 1: The Evolution of Human Resource Systems

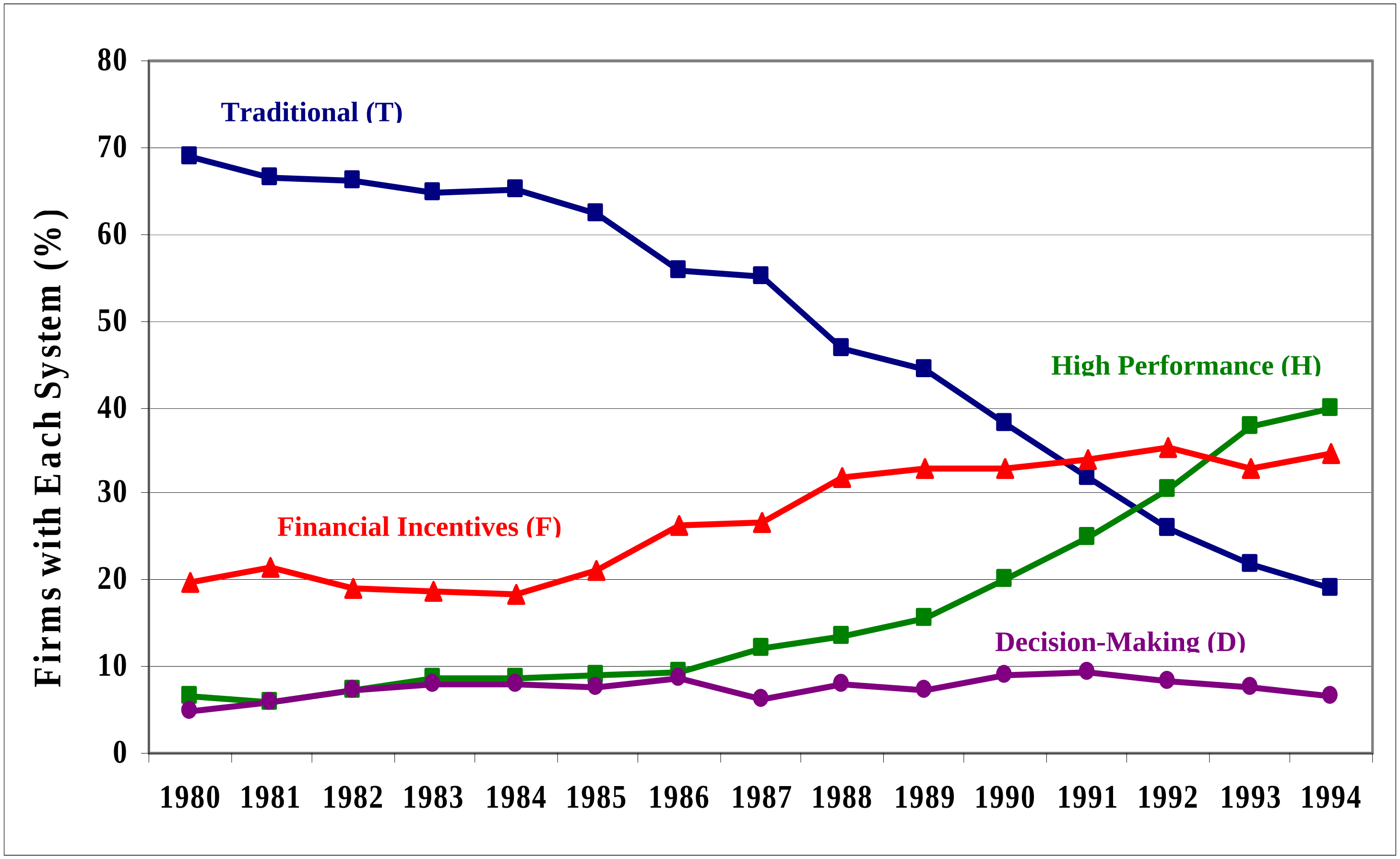


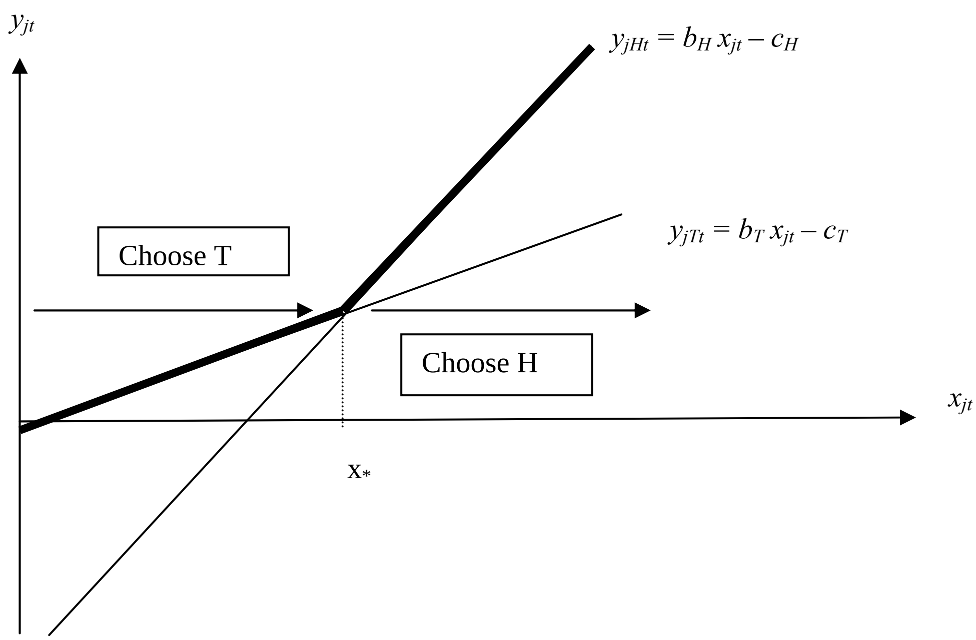
Figure 2: Classification of Human Resource Systems

		Financial Incentives	
		No	**Yes**
Decision-making involvement	**No**	**Traditional system** **Little worker autonomy; Fixed wages**	**Financial incentives system** **Group and firm level incentives and bonuses (e.g., profit sharing, stock ownership)**
	Yes	**Decision-making system** **Employee involvement in decision-making (e.g., work teams)**	**High-performance system** **Group incentives *and* employee involvement**

Complexity

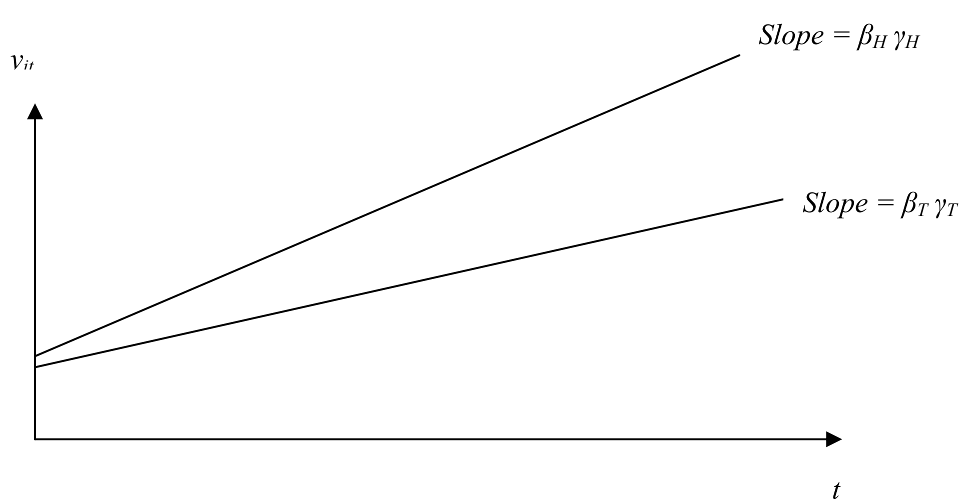
Complexity

Figure 3: Optimal Matching of Firm Capabilities and System



See text for definitions.

Figure 4: Productivity Profiles by System Experience



See text for definitions.

Table 1: Patterns of Change (Transitions) in Human Resource Systems

S_t / S_{t-1}	Traditional		Financial incentives		Decision-making		High-performance		Total	
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
Traditional	313	87.19	32	8.91	8	2.23	6	1.67	359	100.00
Financial incentives	0	0.00	226	90.76	0	0.00	23	9.24	249	100.00
Decision-making	1	2.22	0	0.00	36	80.00	8	17.78	45	100.00
High-performance	0	0.00	3	1.49	2	0.99	197	97.52	202	100.00
Total	314	36.73	261	30.53	46	5.38	234	27.37	855	100.00

Note: S_{t-1} represents the type of human resources system at t-1; S_t is the system in t. Observations reflecting no change in the human resources system between two consecutive years are presented in grey on the diagonal.

Table 2: Logit Estimation of Changes to a More Complex System (from T, D, or F to H, or from T to D or F) vs. No Change in System or Change to a Less Complex System[a]

Variables[b]	LBD	Match-ing	Social learning				All learning mechanisms	
			Distance from		*System distribution and performance*			
			Minneapolis	All other firms	Industry	Ind./age/ size/city[d]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Experience with system T	**-0.0012**						**-0.0017**	**-0.0013**
	(0.0016)						*(0.0014)*	*(0.0015)*
(Experience with system T)^2	**0.00005***						**0.00009***	**0.00006***
	(0.0000)						*(0.0000)*	*(0.0000)*
Experience with system F	**-0.0071****						**-0.0073****	**-0.0053***
	(0.003)						*(0.003)*	*(0.003)*
(Experience with system F)^2	**0.0006*****						**0.0007*****	**0.0004*****
	(0.0000)						*(0.0000)*	*(0.0.000)*
Experience with system D	**-0.0084**						**-0.012**	**-0.004**
	(0.010)						*(0.010)*	*(0.011)*
(Experience with system D)^2	**0.0014****						**0.002*****	**0.007*****
	(0.0004)						*(0.0004)*	*(0.0004)*
Lagged relative performance[c] (Change)		**0.035****					**0.035***	**0.037***
		(0.018)					*(0.019)*	*(0.019)*
Distance from Minneapolis (log)			**-0.014***				**-0.013**	**-0.010**
			(0.008)				*(0.009)*	*(0.009)*
Total distance from other firms (log)				**-0.035***				
				(0.022)				
Lagged system distribution								
Proportion in system F					**-0.122**	**-0.028**	**-0.071**	**-0.002**
					(0.282)	*(0.056)*	*(0.298)*	*(0.053)*
Proportion in system D					**-0.662**	**-0.107**	**-0.753***	**-0.103**
					(0.453)	*(0.092)*	*(0.426)*	*(0.113)*
Proportion in system H					**-0.193**	**-0.172**	**-0.361**	**-0.128**
					(0.369)	*(0.192)*	*(0.376)*	*(0.091)*
Lagged average performance[c]								
Performance system T					**-0.081**	**-0.011**	**-0.060**	**-0.009**
					(0.173)	*(0.050)*	*(0.160)*	*(0.047)*
Performance system F					**-0.138**	**-0.180*****	**-0.136**	**-0.155*****
					(0.138)	*(0.064)*	*(0.137)*	*(0.057)*
Performance system D					**-0.067**	**-0.065**	**-0.046**	**0.022**
					(0.091)	*(0.043)*	*(0.069)*	*(0.049)*
Performance system H					**0.340****	**0.271*****	**0.328****	**0.233*****
					(0.155)	*(0.086)*	*(0.147)*	*(0.085)*
LR Chi2	38.42	34.16	30.81	28.27	49.02	52.07	79.05	67.79
(p-value)	(.000)	(.000)	(.000)	(.003)	(.000)	(.000)	(.000)	(.003)
N	631	631	631	631	631	631	631	631

[a] The dependent variable is 1 for changing to system H from T, D, or F or to system F from T or to system D from T. The dependent variable is 0 for no change in system or a change to system T from system H, D, or F or to system F from H or to system D from H. Note that there are no changes from system D to system F and vice versa. The coefficients reported correspond to marginal effects. Marginal effects were computed following Ai and Norton (2003) using procedure 'predictnl' in Stata. Robust standard errors are in parentheses.

[b] Also includes union and industry dummies, a cubic function of lagged firm size, firm age (unless system experience is used), average real wage at entry in the sample, and year.

[c] Performance is measured using the firm's returns on investment, computed relative to average returns in the firm's industry.

[d] Distribution and average performance of firms with similar industry, age, size, and geographic location (city or not) as $firm_i$.

Table 3: Choice of Human Resources System: Learning-by-Doing

Decisions: / **Variables**[c]	**Switch out of traditional system**[a] **To systems D or F**	**To system H**	**Switch out of decision-making or financial incentives**[b] **To system H**
Firm age[d]	**-0.0009** *(0.0023)*	**0.0002** *(0.0004)*	.
$(\text{Firm age})^2$	**0.000** *(0.0000)*	**-0.000** *(0.000)*	.
Experience with system T	.	.	**-0.002**** *(0.000)*
$(\text{Experience with system T})^2$	.	.	**0.00008***** *(0.00001)*
Experience with system F	.	.	**-0.014***** *(0.001)*
$(\text{Experience with system F})^2$	.	.	**0.0023***** *(0.001)*
Experience with system D	.	.	**-0.012***** *(0.004)*
$(\text{Experience with system D})^2$	.	.	**0.0024***** *(0.0001)*
LR Chi2	32.74		114.92
(p-value)	(0.025)		(0.000)
N	784		662

[a] Multinomial estimations such that the base outcome corresponds to no system change.
[b] Due to the very small number or absence of observations on changes back to the traditional system (from system H or from systems D or F), the choice model in this case is estimated using a logit with two outcomes: no change (in systems D or F) or switch to system H.
[c] The estimation includes union and industry dummies, cubic functions of lagged firm size, firm age (unless system experience is used), average real wage at entry into the sample, and year. The coefficients correspond to marginal effects. The coefficients correspond to marginal effects (see note a in Table 2). Robust standard errors are in parentheses.
[d] Firm age is equivalent to experience with the traditional system for firms currently in system T.

Table 4: Choice of Human Resources System: Matching

Decisions:	Switch out of traditional system[a]		Switch out of decision-making or financial incentives[b]
Variables[c]	To systems D or F	To system H	To System H
(Relative performance change)$_{T-1}$	**0.027**	**-0.000**	**0.040****
	(0.020)	*(0.000)*	*(0.019)*
LR Chi2	76.42		70.20
(p-value)	(0.000)		(0.000)
N	359		294

[a] Multinomial estimations such that the base outcome corresponds to no organizational system change.

[b] Due to the very small number or absence of observations on changes back to the traditional system (from system H or from systems D or F), the choice model in this case is estimated using a logit with two outcomes: no changes (in systems D or F) or switch to system H.

[c] Performance is measured using the firm's returns on investment relative to average returns in the firm's industry. The estimation also includes union and industry dummies, cubic functions of lagged firm size, firm age, and year. The coefficients correspond to marginal effects (see note a in Table 2). Robust standard errors are in parentheses.

Table 5: Choice of Human Resources System: Social Learning

Decisions:	**Switch from the traditional system**[a]								**Switch from D or F to H**[b]			
	(1)		**(2)**		**(3)**		**(4)**		**(5)**	**(6)**	**(7)**	**(8)**
Variables[c]	**To D/F**	**To H**	**To D/F**	**To H**	**To D/F**	**To H**	**To D/F**	**To H**				
Distance from Minneapolis (log)	**0.032****	**0.000**							**-0.004**			
	(0.015)	*(0.001)*							*(0.006)*			
Total distance from other firms (log)			**0.069***	**-0.001**						**-0.013**		
			(0.044)	*(0.004)*						*(0.018)*		
Total distance from system H (log)					**0.071***	**0.000**					**-0.013**	
					(0.040)	*(0.003)*					*(0.018)*	
Lagged system distribution												
Proportion in system F							**-0.361**	**0.003**				**0.496**
							(0.392)	*(0.055)*				*(0.438)*
Proportion in system D							**-0.667**	**0.079**				**-0.370**
							(0.706)	*(0.096)*				*(0.730)*
Proportion in system H							**-0.218**	**-0.080**				**0.085**
							(0.668)	*(0.141)*				*(0.529)*
Lagged average performance[d]												
Performance system T							**0.131**	**-0.037**				**-0.156**
							(0.260)	*(0.048)*				*(0.169)*
Performance system F							**0.187**	**-0.052***				**-0.145**
							(0.366)	*(0.032)*				*(0.143)*
Performance system D							**-0.403**	**-0.016**				**-0.057**
							(0.303)	*(0.054)*				*(0.086)*
Performance system H							**0.071**	**0.124***				**0.357**
							(0.295)	*(0.070)*				*(0.236)*
LR Chi2 (p-value)	70.10		62.81		64.68		90.10		44.19	44.75	44.66	104.98
N	784		784		784		358		662	662	662	294

[a] Multinomial estimations such that the base outcome corresponds to no organizational system change.

[b] Due to the very small number or absence of observations on changes back to the traditional system (from system H or from systems DM or F), the choice model in this case is estimated using a logit with two outcomes: no changes (in systems DM or F) or switch to system H.

[c] The estimation includes union and industry dummies, cubic functions of lagged firm size, firm age (unless system experience is used), average real wage at entry in the sample, and year. The cubic terms for experience (or age) are not shown for space consideration. When experience (or age) is significant, the cubic term is significant and of the order of 10^{e-06} or smaller. The coefficients correspond to marginal effects (see note a in Table 2). Robust standard are errors in parentheses.

[d] Performance is firm's returns on investment relative to average returns in the firm's industry.

Table 6: Timing of Human Resources System Change

Hazard Analysis of Adoption of More Complex Systems[a]

Variables[b]	'Failure' = System H			'Failure' = System D or F		
	Cox	**Exponential**	**Weibull**	**Cox**	**Exponential**	**Weibull**
Union	**0.223**	**0.307**	**0.351**	**-0.290**	**-0.334**	**-0.331**
	(0.383)	*(0.384)*	*(0.382)*	*(0.329)*	*(0.331)*	*(0.331)*
Manufacturing	**0.458**	**0.510**	**0.496**	**0.034**	**0.016**	**0.013**
	(0.364)	*(0.380)*	*(0.380)*	*(0.273)*	*(0.273)*	*(0.274)*
Service	**0.047**	**0.147**	**0.105**	**0.142**	**0.116**	**0.118**
	(0.481)	*(0.477)*	*(0.479)*	*(0.345)*	*(0.345)*	*(0.345)*
Firm's birth year (relative to 1980)[c]	**-0.016****	**-0.015****	**-0.016****	**-0.009***	**-0.008***	**-0.009***
	(0.006)	*(0.006)*	*(0.006)*	*(0.004)*	*(0.005)*	*(0.005)*
Firm size (log)	**0.400*****	**0.263*****	**0.243*****	**0.181***	**0.052**	**0.049**
	(0.004)	*(0.090)*	*(0.093)*	*(0.103)*	*(0.071)*	*(0.071)*
Distance from Minneapolis (log)	**0.085**	**0.086**	**0.085**	**0.242****	**0.298****	**0.300****
	(0.149)	*(0.148)*	*(0.148)*	*(0.121)*	*(0.124)*	*(0.124)*
Average real wage (log)[d]	**0.432***	**0.364***	**0.422***	**0.069**	**0.101**	**0.105**
	(0.227)	*(0.224)*	*(0.224)*	*(0.166)*	*(0.164)*	*(0.164)*
Log likelihood	**-318.0**	**-160.2**	**-156.8**	**-518.90**	**-318.0**	**-229.9**
LR Chi2	21.50	18.71	19.24	15.88	15.56	15.75
(p-value)	(.010)	(.016)	(.013)	(.069)	(.010)	(.046)
N	1419	1419	1419	974	974	974

[a] The dependent variable is time to a switch to system H in the left panel and to a switch to systems D or F in the right panel.
[b] Also includes a dummy indicating whether the firm is within a 10-mile radius of the center of Minneapolis. Robust standard errors are in parentheses.
[c] This variable is computed as 1980—the year the company was founded. It is therefore an increasing function of firm age.
[d] This variable corresponds to average real wages in the company in 1980 or at birth if born after 1980.

Table 7: Learning-by-Doing Effects[a]
Performance Dynamics for Non-Changers and for Changers After a Change, by System

Dependent Variable: ROI

Variables[b]	Sample of non-changers and observations post-change for changers[c]		
	Sys T	**Sys H**	**Sys F**
Experience with system	**-0.0046**	**0.039****	**-0.032****
	(0.010)	*(0.018)*	*(0.014)*
(Experience with system)^2	**0.000**	**-0.002***	**0.001**
	(0.000)	*(0.000)*	*(0.000)*
R^2	0.17	0.10	0.11
N	124	252	223

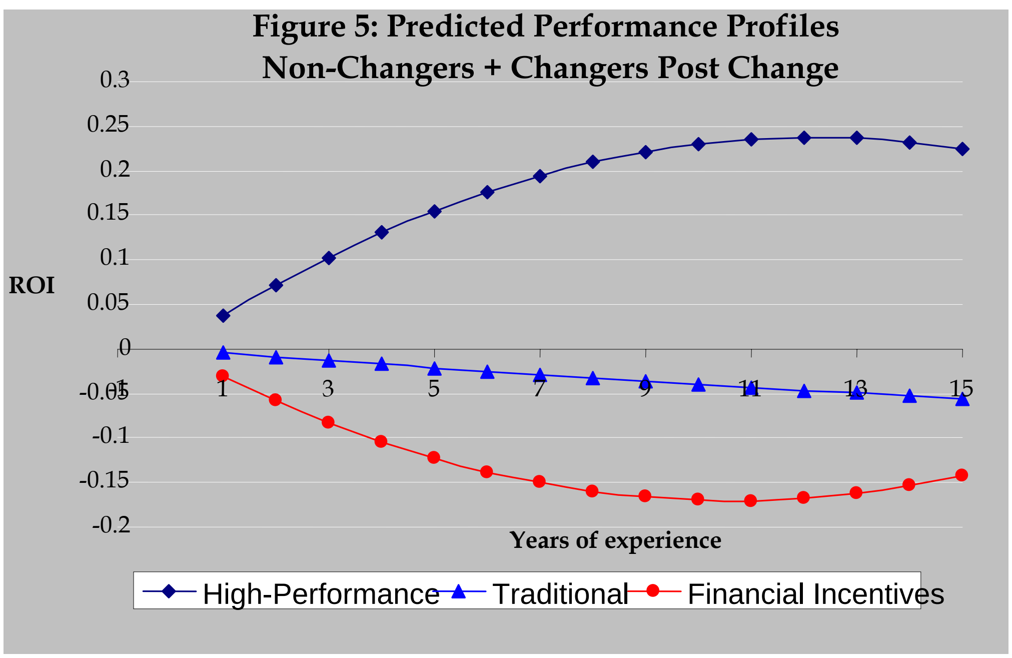


Figure 5: Predicted Performance Profiles
Non-Changers + Changers Post Change

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[a] The dependent variable is returns on investment.
[b] All regressions include a union dummy, year dummies for 1980–1994, industry dummies, and firm size. Robust standard errors are in parentheses.
[c] There no observations of non-changers in the decision-making system and too few observations of changers to this system, and therefore the results for system D are not shown.
[d] Predicted performance profiles using the estimates in Table 7. "Years of experience" reflects the number of years of experience with a given system.

Appendix A

Table A1: Summary Statistics

Variable	All Firms Mean	All Firms Std. Errors	Public Firms Mean	Public Firms Std. Errors
Firm characteristics				
Firm age (years in business)	33.91	0.31	28.32	0.97
Firm size (number of employees)	306.93	17.84	1351.85	141.57
Publicly traded statue (dummy)	0.22	0.00	1.00	0.00
Unionization (dummy)	0.22	0.00	0.20	0.01
Manufacturing (dummy)	0.46	0.01	0.71	0.02
Trade (dummy)	0.35	0.01	0.15	0.01
Service (dummy)	0.20	0.00	0.14	0.01
Average real wage (first year in sample)	18044.05	129.21	23485.29	528.74
Distance to Minneapolis	38.75	0.71	20.96	1.40
Distance from Other Firms	45524.34	430.19	36141.99	808.90
Experience with system				
Experience with traditional system	24.90	0.31	20.58	0.87
Experience with decision-making system	1.61	0.05	1.88	0.14
Experience with financial incentives system	5.48	0.10	4.34	0.30
Experience with high-performance system	1.92	0.08	1.52	0.23
Performance measures				
ROI			.006	.01
Relative ROI			.072	.01
Lagged relative ROI level			.079	.01
Lagged relative ROI change			-.013	.01
Number of observations	7896		855	
Number of firms	690		110	

Sample size – publicly-traded firms

Table A1 provides summary statistics for the sample with non-missing information on the ROI variable and including “stayers” in the high-performance system. The sample size with all observations on firm characteristics including the performance measure ROI is 855 observations (110 firms). For the analysis in Table 2, estimating the likelihood of switching to a *higher* performance system, we (1) dropped observations on firms in the high-performance system after a switch to that system throughout the remaining of the sample period and also excluded firms that started with the high-performance system and kept it throughout the entire period. Given that there is no higher performance system to switch to for these firms, it is logical to drop them from the analysis in this case. The sample size drops down to 631 observations. For the analyses in Tables 3 and 5 estimating the likelihood of switching *out of* a given system, the original dataset of 855 observations is further divided into the sample of observations on firms with the traditional system potentially switching to a higher performance system (either D, F, or H) which contains 784 observations and the sample of firms with either the decision-making system or financial incentives system potentially switching to the high-performance system which contains 662 observations. For the analysis in Table 4, these two samples drop in size because we use the second lag of changes in the performance for ROI. The hazard analysis in Table 6 is based on a larger sample of all publicly-traded firms because this analysis does not require information on performance.

Table A2: Logit Estimation of Changes to a More Complex System vs. No Change in System or Change to a Less Complex System[a] , All Firms

Variables[b]	LBD	Social learning				All learning mechanisms	
		Distance from		*System distribution and performance*			
		Minneapolis	All other firms	Industry	Ind./age/ size/city[d]		
	(1)	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Public Firm Dummy	**0.0172****	**0.0196*****	**0.0197*****	**0.0173****	**0.0150**	**0.0150***	**0.010**
	(0.08)	*(0.008)*	*(0.008)*	*(0.009)*	*(0.012)*	*(0.009)*	*(0.011)*
Experience with system T	**-0.0003**					**-0.0004**	**-0.0005**
	(0.0002)					*(0.0002)*	*(0.0004)*
(Experience with system T)^2	**0.0000**					**0.0000**	**0.0000**
	(0.0000)					*(0.0000)*	*(0.0000)*
Experience with system F	**-0.0021*****					**-0.0024*****	**-0.0048*****
	(0.0008)					*(0.001)*	*(0.002)*
(Experience with system F)^2	**0.0001*****					**0.0002****	**0.0004****
	(0.0000)					*(0.0001)*	*(0.0002)*
Experience with system D	**-0.0016**					**0.002**	**0.013****
	(0.0012)					*(0.002)*	*(0.006)*
(Experience with system D)^2	**0.0000**					**-0.0001**	**0.000**
	(0.0001)					*(0.000)*	*(0.001)*
Distance from Minneapolis (log)		**-0.000**				**-0.002**	**0.001**
		(0.002)				*(0.002*	*(0.009)*
Total distance from other firms (log)			**0.000**				
			(0.005)				
Lagged system distribution							
Proportion in system F				**0.010**	**-0.010**	**0.022**	**0.053**
				(0.075)	*(0.041)*	*(0.074)*	*(0.044)*
Proportion in system D				**0.139**	**-0.160***	**-0.128**	**-0.211*****
				(0.135)	*(0.069)*	*(0.134)*	*(0.077)*
Proportion in system H				**0.153**	**-0.064**	**0.136**	**-0.030**
				(0.119)	*(0.056)*	*(0.118*	*(0.055)*
Lagged average performance[c]							
Performance system T				**-0.017**	**-0.024**	**-0.008**	**-0.049**
				(0.049)	*(0.047)*	*(0.050*	*(0.043)*
Performance system F				**-0.034**	**-0.039**	**-0.024**	**-0.011**
				(0.045)	*(0.050)*	*(0.046)*	*(0.047)*
Performance system D				**-0.056***	**-0.015**	**-0.052***	**-0.004**
				(0.034)	*(0.036)*	*(0.032)*	*(0.031)*
Performance system H				**0.112****	**0.079***	**0.095****	**0.069***
				(0.043)	*(0.047)*	*(0.044)*	*(0.045)*
LR Chi2	139.65	121.48	121.75	87.28	56.01	100.54	92.14
(p-value)	(.000)	(.000)	(.003)	(.000)	(.000)	(.000)	(.003)
N	6554	6554	6554	5154	2161	5154	2161

[a] The dependent variable is 1 for changing to system H from T, D, or F or to system F from T or to system D from T. The dependent variable is 0 for no change in system or a change to system T from system H, D, or F or to system F from H or to system D from H. Note that there are no changes from system D to system F and vice versa. The coefficients reported correspond to marginal effects. Marginal effects were computed following Ai and Norton (2003) using procedure 'predictnl' in Stata. Robust standard errors are in parentheses.

[b] Also includes union and industry dummies, a cubic function of lagged firm size, firm age (unless system experience is used), average real wage at entry in the sample, and year.

[c] Performance is measured using the firm's returns on investment, computed relative to average returns in the firm's industry.

[d] Distribution and average performance of firms with similar industry, age, ze, and geographic location (city or not) as $firm_i$.