Learning: What and How?

An Empirical Study of Adjustments in Workplace Organization Structure

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Abstract

In this paper we seek to understand how firms learn about what adjustments they need to make in their organization structure at the workplace level. We define four organizational systems: traditional (the simplest system), high-performance (the most complex system), decision-making oriented, and financial-incentives oriented (intermediate complexity). We analyze (1) the effects of learning-by-doing on adoption of more or less complex systems, (2) the shape of the performance-experience learning curves associated with different systems, (3) the match between perceived organizational capabilities and the choice of systems, (4) the influence of other firms' systems and performance on a firm's adjustment decisions, and (5) the effect of a firm's location on its decisions.

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1. Introduction

The period from the early 1980s to the middle of the 1990s was characterized by rapid change, with rising globalization, heightened competition, political change, and rapid product and process technological change. To succeed or just to survive in this environment, many firms adjusted their organization structure. At the level of the workplace, the change was frequently reflected in decentralization of decision-making and increased reliance on financial incentives (Appelbaum and Batt, 1994, Cappelli et al., 1997).

Organizations are under constant competitive pressure to improve their organization structure in order to get workers and managers to perform better. How to do better consists of many elements, two of which are central to understanding organizational change: identifying practices that impact behavior in desirable ways, and figuring out how to combine various practices to obtain maximum synergy among them. In a world of full and perfect information, unboundedly-rational managers would implement all available knowledge instantaneously and therefore organizations would always be in internal and external equilibrium. The large literature that documents change in actual organizations suggests that, in reality, managers struggle to figure out what works and how to implement change in their organizations, and that the process is often a protracted one. This process may be summarized as learning.

There is a substantial literature on organizational learning.[1] The literature identifies three dominant learning mechanisms. In *learning-by-doing*, decision-makers learn from their experience to improve their ability to operate a system (Yelle, 1979; Argote and Epple, 1990). In *matching*, decision-makers extract information about their firm's capabilities or absorptive capacity to operate a particular system (Cohen and Levinthal, 1990; Jovanovic and Nyarko, 1995, 1996). In *social or vicarious learning*, decision-makers learn from observing the behavior of others (March, 1991, Haunschild and Miner, 1997; Foster and Rosenzweig, 1995).

In this paper, we investigate an original and unique dataset to test the influence of these learning mechanisms on how firms adjusted their organization structure at the level of the workplace during the period of early 1980s to the mid-1990s. We define organization structure on the basis of decision-making and incentive practices, which we combine into four *organizational systems*: traditional (or simple, with centralized decision-making with fixed pay), high-performance (innovative or complex, decentralized decision-making and variable pay), and intermediate,

[1] For example, Ichniowski and Shaw (1995) study why older firms take longer to adopt new practices, Pisano, Bohmer and Edmonson (2001) and Edmondson, Winslow, Bohmer and Pisano (2003) analyze learning from organizations in the health care industry, Sorenson (2003) focuses on the effect of a firm's internal structure on learning outcomes among computer workstation manufacturers, Schwab (2007) looks at the relative impact of multilevel sources of information on adoption of an innovative managerial practice, and Rahmandad (2008) analyzes the impact of delays between actions and payoffs on learning in a simulated organization (earlier literature on organizational learning is reviewed by Argote, 1999).

decision-making and financial incentives. We study firms' choices with respect to these systems: adding, shedding and keeping practices. 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 practices concerning the group and firm-level decision-making and financial incentives, which we combined into the four systems.

Figure 1 documents the significant decline in the proportion of firms with a traditional system and the rise in the proportion of firms that have a high-performance or financial incentives system. The figure reflects the cumulative result of the choices made by each sample firm over time, the choice being between continuation with the current organizational system and switching to another system. Table 1 summarizes these choices and shows the disposition of the 855 annual decisions that were made by the sample of publicly-traded firms between 1980 and 1994.[2] A majority of the firms (72.7%) had changed systems, with some more than once. Most transitions were from the traditional into the financial incentives system, and from financial incentives into the high-performance system. Since we do not observe learning directly, we examine these choices-transitions 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.

This is the first paper to evaluate a wide spectrum of variables and firm characteristics that influence learning during the 1980s, a period of major transformation in firm organizational structures. We allow for the possibility that firms learn in multiple ways and from multiple sources of information, internal (accumulation of experience and changes in performance) as well as external (industry-level adoption rates and average performance, distance to largest city).[3] We also examine the effects of different learning mechanisms on financial performance. A sizable literature has investigated the determinants of adoption of human resource systems, but our dataset permits to analyze the *timing* of adoption and its consequences on firm performance.[4]

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 3, we

[2] Most of the analysis in the paper focuses on public firms for which we have financial performance information needed for understanding the matching mechanism and learning curves. In an appendix, we present analysis of learning by-doing and social learning in private firms, where no financial information is required.

[3] Zimmerman (1982), Irwin and Klenow (1994), Henderson and Cockburn (1996), Thompson and Thornton (2001) and Schwab (2007) adopted a similar approach of simultaneously analyzing different sources of learning. They focused on the effects of learning from a firm's own experience relative to learning from its competitors. Our study extends their approach to include a larger set of learning mechanisms. Moreover, by analyzing firms in a cross-section of industries, our results generalize beyond single-industry or single-firm learning phenomena.

[4] The literature investigates why firms have certain organizational practices or systems and how these affect performance, rather than the *process* through which they come to adopt those practices; see, for example, Osterman (1994), Jones and Kato (1995), Ichniowski, Shaw, and Pernushi (1997), Cappelli and Neumark (2001).

describe the data and in section 4 we detail our analytical framework and empirical strategy. The results are described in section 5, and in section 6 we conclude with a discussion of the implications of our findings for the understanding of learning by organizations as well as for further research.

2. Learning by Organizations: Discussion and Hypotheses

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, certain management practices must be put in place to meet an organization's needs and capabilities. 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. Three different approaches to learning have been developed in the literature. 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, such as organizational structure. We develop the three approaches with reference to learning about organization structure, which we discuss briefly below before turning to the three learning mechanisms.

2.1 Organizational structure in the workplace

The allocation of decision-making and financial returns is considered in the economics-inspired literature as the central element of organizational structure (e.g., Hart and Moore, 1990, Ben-Ner and Jones, 1995 and Brickley et al., 2007). Focusing on these elements, we distinguish among four organizational 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.[5] Moving away from the traditional system entails a move to a more complex management challenge. There are alternative ways of aggregating diverse

[5] These four systems are equivalent to cells OA1-OA4 in Table 1 of Ben-Ner and Jones (1995).

practices into systems; these four systems may be complemented by additional practices, such as total quality management, training, monitoring, employment security and more (Prendergast, 2002 and Ben-Ner, Kong and Lluis, 2007); we discuss alternative categorizations of systems in section 5.5.1.

The four systems differ in terms of the organizational capabilities necessary for their effective operation, the costs of operating them, and the benefits that stem from their operation. *Organizational capabilities* concern 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 (Nelson and Winter, 1982, Chandler, 1992). Organizational capabilities reflect the ability of managers to select mechanisms for allocation of decision-making, incentives to induce employees and managers to act in the organization's interests and to put in place supporting practices such as training and organizational culture to promote a sense of duty and dedication to ameliorate 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; training or replacement may enhance organizational capabilities, but the fact that hiring and training are commonly done by existing staff prevents significant transformation of a firm's capabilities, resulting in a nearly fixed level of organizational capabilities.[6] Organizational capabilities also relate to the firm's absorptive capacity, the ability of a firm to recognize and assimilate the value of new information (Cohen and Levinthal, 1990).

The *costs* required to operate a system effectively rise with its complexity (Ichniowski and Shaw, 1995). The high-performance system is the most costly because it requires both investments in training to enable employees to make sound decisions and financial resources to provide effective incentives. The decision-making and financial incentives systems entail 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. The magnitude of the *benefits* a firm can reap increases with organizational capabilities. Poor management can cause severe performance problems, and the more complex the system the more severe are the problems. 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 in equilibrium a high-capability firm performs best, that is, generates the largest net benefits with the high-performance system, whereas a low-capability firm performs best when it employs the traditional system. The intermediate systems

[6] In a study asking respondents in U.S. and Japanese semiconductor firms to rate the importance of different sources of information affecting decision-making, the most important source of information in both countries was colleagues in their own company (Appleyard, 1996).

yield greater benefits when supported by appropriate organizational capabilities, which rank in between the levels required by the traditional and high-performance systems.

The decision-making system cannot operate effectively without the complement of financial incentives because self-interested employees and management may use their decision-making power to pursue activities that benefit them rather than the organization (Levine and Tyson, 1990). Similarly, a financial system may provide appropriate incentives but in the absence of decentralization and delegation of decision-making employees and managers cannot act on their incentives. Only the high-performance system can take advantage of the complementarity between financial incentives and decision-making delegation; an intermediate system will perform worse than a high-performance system and possibly worse even than the traditional system (Ben-Ner and Jones, 1995, Appelbaum et al., 2000).

Why would a firm adopt an intermediate system? 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 myriad relationships among employees (Gant, Ichniowski, and Shaw, 2002). Firms with limited organizational capabilities or strong internal resistance to change will not make the transition in one leap; instead, they will move temporarily to an intermediate system, and then move on to the high-performance system. This is compatible with the two-stage transitions observed in Table 1.

2.1 Learning-by-Doing

Arrow's (1962) seminal contribution 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 (Epple, Argote and Devadas, 1991, Cabral and Leiblein, 2001).

Learning from experience enhances organizational capabilities. It may improve an organization's ability to exploit more productively its *current* system, in line with the principal predictions of theory. Experience may also generate organizational knowledge that enables a firm to operate a more system than the firm's current system and thus be able to take advantage of its greater productivity. For a firm that accumulates knowledge that is transferable to more complex systems, as its capabilities grow over time, at some point they will reach the threshold level for switching to a more complex system.

Learning-by-doing has implications for the dynamics of firm performance. The typical learning curve exhibits an initial period of adjustment to the new system, after which productivity increases with experience but at a decreasing rate and eventually levels off. Firms with different capabilities accumulate experience at different rates, leading to different learning curves. Therefore the productivity profiles of firms with the high-performance system should be above the profile of firms with the traditional system – assuming that they adopted the systems that match their capabilities.[7]

The discussion above focused, for the sake of presentational convenience, on the traditional and the high-performance systems. The discussion can be extended to the four systems. The decision-making and financial systems are more complex than the traditional system but less so than the high-performance one, but the two intermediate systems cannot be ranked and we will treat them as equally complex, and extend the predictions derived for the two systems to include the third intermediate possibility. Formally:

Hypothesis 1: *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**).The productivity profile of firms matched with the high-performance system is above the productivity profile of firms matched with the less complex system (**H1c**).*

2.3 Learning About the Match Between a Firm's Abilities and its System

How do managers learn about their firms' ability to operate different systems? The Bayesian learning literature suggests that managers have some prior beliefs about their firms' organizational capabilities and update them using signals they receive over time.[8] If the perceived capabilities exceed a certain threshold, management will decide to switch to a more complex system; otherwise it will stay with the current one. Managers update their beliefs on the basis of signals they extract from observing previous performance: a switch to a more complex system will follow improvements in performance, if those are large enough to bring expected capabilities above the threshold for switching systems. Formally:

[7] The idea that firms in the same industry vary in their learning rates was first illustrated by Dutton and Thomas (1984), documented across different plants of the same firm using the same technology by Chew, Bresnahan and Clark (1990) and by Pisano, Bohmer and Edmondson (2001) for cardiac surgery departments implementing a new technology.

[8] This literature was initiated by Jovanovic (1979) concerning worker mobility and later applied to firm behavior in Jovanovic (1982) and Jovanovic and Nyarko (1995) and to firm choice of technology in Jovanovic and Nyarko (1996). This is similar to the idea of performance feedback, according to which firms adjust a given practice incrementally based on performance (Greve, 2003). Gibbons and Waldman (1999) analyze a model of learning based on time-dependent shocks in which promotion decisions arise following previous period improvements in worker performance.

Hypothesis 2 (H2): *The likelihood of switching to a more complex system increases with improvements in performance.*

2.4 Social learning

Firms adjust their organizational structure not only by looking inward at their own experiences, but also by learning effective management practices from consultants, colleagues in professional organizations, and academics, as well as observing the actions of other firms. 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 the traditional system do not know precisely the costs and benefits of the high-performance system, and therefore do not know the threshold level of organizational capabilities that a firm must possess in order to make a successful switch.

Managers may emulate other firms also to gain legitimacy with employees, customers, suppliers, and others on whom they depend (DiMaggio and Powell, 1983). 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.

The information managers seek and the value of what they learn from others may be correlated with their firms' abilities. Large firms enjoy economies of scale in collecting information about their environment. 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 - conferences, professional enhancement courses, consultants, academics, and higher-quality managers and employees—compared to firms located farther away (Epple, Argote and Murphy, 1996, Audretsch and Lehman, 2005).

Information pertaining to a firm's own industry is more valuable than information from other industries, which may have different economic and technological circumstances. A relatively simple indicator of what other firms do is captured by the prevalence of firms using different systems. A richer (but harder to obtain) signal is the performance of firms with different systems, especially in a firm's own industry (Haundschild and Miner, 1997). Formally:

Hypothesis 3. *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 firms practicing that* *system (**H3d**). The effects are weaker when the system proportion and performance measures concern other industries as compared to the firm's own industry (**H3e**).*

The three mechanisms may be used by the same firm as it seeks to learn about its own organizational capabilities and the costs and benefits of alternative systems, and from its own experience. The hypothesis testing in the next section allows explicitly for this possibility.

3. Data and Variables

3.1 The Dataset

We assembled a rich dataset concerning more than 800 privately-held and publicly-traded firms. The variables used in the analysis are summarized in the Appendix, where a discussion of sample size differences across various estimations is also provided. For coherence and completeness of analysis, we focus our attention on the sample of publicly-traded firms for which we have financial information, our performance outcome. We replicated the analysis for the full sample of firms and report the main results but do not include them in the paper (they are available upon request). The description of the dataset below focuses on the publicly-traded firms. We obtained data on various management 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.

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 firms that did not respond. The overall response rate was 61% (177 firms), a rate that exceeds that of most similar surveys. The survey asked for information about current practices in the responding firms as well as retrospective information regarding the dates of introduction and discontinuation of various practices.[9] For each responding firm we thus had variables indicating the presence or absence of various human resource practices over time as well as the introduction and discontinuation dates, where applicable, of these practices. For each firm we merged, when available, financial data from Compustat and employment and average wage data from UI files. Because the UI data were available only from 1980 on, we confined our analysis to the period from 1980 to the year of the survey, but when we use experience variables (how long a practice was in place), we employ the actual date when a practice was introduced, even if that was prior to 1980. The sample period is

[9] 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 colleagues' recollections.

therefore 13 years (the use of *lagged changes* in firm performance implies that we lose two years of data). Our panel dataset is anchored in the year of the survey and its size gets smaller the further we go back away from 1994.[10] Among the 110 firms with all the requisite data (as compared to the 177 responding firms), there were 39 firms in 1980, with others having been established in later years. Firms may enter and exit the sample relative to the annual availability of financial data (ROI, the most limiting variable in our dataset). Consequently, a firm is in the sample for an average of 7.8 years.

3.2 Variables

We constructed the dummy variables that represent the four 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). 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.

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). It is important to keep in mind the differential effects of time and experience when modeling the effect of learning-by-doing with a system on decisions to adopt more complex systems. Experience with a system can start only when the practices that define it become available. The innovative practices

[10] Some of the firms that went out of business before the 1994 survey were likely poor performers who, among other things, did not adjust their systems as well as surviving firms. Hence analysis of adjustment by survivors will likely show a stronger pattern than that of non-survivors.

became available in early to mid-1980s, which is when our sample period starts. As a result, the system with which firms have most experience is, of course, the traditional system, whereas the high-performance system, being the most recent, has been in use least. All our estimations include year effects and control for firm age to capture the effect of time independently of the system effects. For *matching*, we use the lagged difference in relative returns on investment (ROI). To compute the relative returns, average ROI in the firm's industry was subtracted from the firm's own ROI. We use the one digit SIC industry classification to define industries.

For *social learning*, we use a firm's total distance to other firms as a measure of its isolation and networking opportunities.[11] To capture opportunities for learning from other sources as well as for networking, we use a firm's distance to downtown Minneapolis. Minneapolis is the state's main metropolitan center, where several important institutions that provide opportunities for networking or transfer of knowledge are located. We characterize information about other firms' systems by computing the prevalence (distribution) of systems and the average performance of firms by system in a firm's own industry, as well as in other industries. Firms may rely more on information about firms that are more similar to them, so we created these two measures also for firms with similar size, age, and similarly located within 10 miles of Minneapolis.[12]

In our analyses we control for firm size, industry and unionization status.[13] We also use information about firm average real wage to control for firm heterogeneity; to deal with potential endogeneity, we use a firm's average real wage only in the year the firm entered the sample.

The system variables are based on retrospective data. The use of retrospective data may cause two kinds of recall errors: memory effects (forgetting that some events took place) and telescoping effects (incorrectly placing an event on the time axis). Forward telescoping (i.e., reporting an event as occurring closer to the survey time than was actually the case) usually prevails because subjective experience of time is shorter than actual time. This implies a downward bias in the reported length of spells in progress at the time of survey (Torelli and Trivellato, 1993). Measurement errors in the dependent variable of either kind will not bias our analysis of learning about the match and learning from others, where *switching* is the dependent variables because the distortion process is random and is not likely to be associated with firm characteristics (firm size, industry, and various practices that were in place at the time of the survey). Analysis of learning-by-doing involves the use of experience with a system and therefore it is likely to be affected by

[11] 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.

[12] 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).

[13] To minimize the number of right-hand side variables, industry controls are based on a broader definition of industry (service, trade and manufacturing) than the one digit SIC classification.

telescoping effects (Torelli and Trivellato, 1993). The associated estimates presented therefore may suffer from a downward bias, which makes it more difficult to capture learning-by-doing effects and therefore easier to reject H1.

4. Empirical Strategy

Learning is not observable; we can only identify the consequences of learning, the presence or absence of system change at a given point in time as well as changes 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 or not 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 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.

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:

$$P(S_t|S'_{t-1}) = F(exp_{ts}) + \beta \Delta y_{jt-1} + \lambda_1 I_{Nothers\ at\ t-1} + \lambda_2 I_{Pothers\ at\ t-1} + \lambda_3 \log(1+ Dist_{city})) + \varepsilon_t\,, \qquad (1)$$

where S_t is the new system and S'_{t-1} is the previous system, F is a non linear function of experience with a system reflecting the learning-by-doing effect, β corresponds to the matching effect, and the social learning effects are represented by λ_1, the effect of previous-period information about the distribution of firms $I_{Nothers}$, $\lambda_{2,}$ average performance by system $I_{Pothers}$,[14] $\lambda_{3,}$the effect of the distance of the firm to Minneapolis[15], and ε_t is a random noise.

We implement this general framework in two ways, balancing generality with data restrictions. We first estimate the likelihood of a *change to a more complex system* (from T to F, D,

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

[15] 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.

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 (1).[16] In this logit estimation, the probabilities of adjusting systems are independent of a firm's current system. The results are presented in Table 2. We next investigate the different learning effects by estimating conditional probability frameworks by the type of a firm's current system. 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 (D or F), and learning about a firm's own capabilities may be more important for the decision to switch out of T than learning about costs and benefits of a system by observing other firms' information. We perform multinomial estimations of the likelihood of switching out of T either into D or F, and logit estimations for the likelihood of switching out of D or F into H.[17] Results are presented in Table 3.

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 a firm's ROI on a quadratic function of system experience, controlling for industry, union, and firm size. Firm heterogeneity and matching effects on the learning curve are handled by comparing the profiles of firm performance across systems. To take into account the compositional bias in the estimation of the performance profile for a given system caused by the fact that firms adopt or switch 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 during the sample period as well as on observations *after* switching to a new system. The non-changers (i.e., firms that report the same system since 1980 or since they entered the sample if born after 1980) and the post-change firms are assumed to be matched correctly with their system 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 the effects of matching organizational capabilities to systems. Results are presented in Table 4 and Figure 3.

5. Results

5.1 Learning-by-Doing, Matching, and Social Learning

The results in column (1) in Table 2 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 F system; the effect for

[16] As Table 1 indicates, very few changes are made to a lower-complexity system, so these cannot be evaluated separately.
[17] 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.

D is similar but less precisely estimated, and the effect for the T system is still 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. It takes 12 years of accumulated experience for experience with T to increase the likelihood of switching to a more complex system, while it takes only 5.9 years for experience with F and three years for experience with D 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 expertise depends on a firm's current system: it takes longer to be ready to switch out of T than from D or F. These results imply that hypothesis H1a is supported.

The result in column (2) suggest that previous-period changes in performance increase the likelihood of switching to a more complex system; past improvements in a 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, as predicted by hypothesis H2.

The estimates on social learning variables are in columns 3 and 4. Greater distance from Minneapolis as well as greater distance from other firms reduce the likelihood of switching to a more complex system (columns 3a and 3b), in line with hypotheses H3a and H3b. 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, contradicting H3c. Information about firms' average performance under the H system increases the likelihood of adopting a more complex system, as predicted by hypothesis H3d. However, information about the F system's performance contradicts this hypothesis, as does (more weakly) information about the D and T systems. In column 4c, we use the system distribution and performance measures from firms in industries outside the firm's own industry. Compared to the measures based on the same industry as in column 4a or similar industry, age and location as in column 4b, none of the effects are significant for explaining firms' switching decisions. In addition, the value of the LR statistics shows a poor fit of this model specification with the data (p-value of .13). Together, these results are consistent with the idea that social learning effects are stronger when information is drawn from firms more similar in production technology as opposed to firms in different industries (H3e). Thus social learning seems to operate through favorable information from similar firms about performance effects of the H system, and better-located firms appear 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 (5a) corresponds to social learning variables as specified in column (4a), and column (5b) corresponds to the specification of column (4b). For space reasons, we show the results with distance to Minneapolis variable; the other distance variable's effects were similar to those estimated in columns (3) and (4) with slightly weaker significance levels. 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 available upon request). 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 estimated coefficients. The effects, however, are smaller. 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 A). These results suggest that privately-held firms tend to be more traditional and conservative; they may be less prone to adjustments in their organizational system and therefore are less sensitive to learning opportunities.

5.2 Learning Mechanisms by Current System

Table 3 presents results of a multinomial analysis for firms with the T system considering the decision to stay with it or to switch to the D or F system, or to the H system, and results of a logit analysis for the decision to stay with or to switch from the D and F systems into H.[18]

In the case of learning-by-doing, there is no significant effect of experience with T[19] on the likelihood of switching out of it, neither to D or F nor to H. Consistent with the results in Table 2, H1a is not supported for T. For firms that have already the D or F system, the likelihood of switching to the H system (right panel) is affected significantly by experience with D and F (no significant effect of experience with T). This result is consistent with the evidence for computer manufacturers that learning-by-doing with T does not have an effect on switching decisions but learning-by-doing with D or F does (Sorenson, 2003). Similar to the results in Table 2, it takes 3.47 years for experience with D and 2.38 years for experience with F to lead to a switch to H. Hypothesis H1a is thus strongly supported for experience with F and weakly for experience D.

[18] 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.
[19] With one exception, all the firms with T 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.

Past changes in performance have no significant effect on the decision to switch out of the T, but do for switching from the D and F systems into the H system. These results suggest that improvements in past performance serve as a signal of greater capabilities only for firms that have already implemented an intermediate system. The matching results in Tables 3 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 capabilities. As a result of its inclusion, there may be no more variation left to be explained by past performance changes that also reflect firm capabilities.

For social learning, distance to Minneapolis has a negative effect on the likelihood of switching out of T to D or F but not to H. The coefficient is of similar magnitude as the one estimated in Table 2 but the standard error is much larger due to the drop in sample size. Distance to Minneapolis has no significant effect on the likelihood of switching to H from D or F (second column of Table 3). This suggests the possibility that distance away from sources of information about how to use the H 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 H system.

The distribution of systems in a firm's own industry does not have a statistically significant effect on the decision to switch from T to either D or F or to H. However, the performance of firms in a firm's own industry does have an effect on the switch from T to H but not to the intermediate systems. Specifically, the better the average performance of firms using H, the greater is the likelihood of switching to it.[20]

Firms with the intermediate systems (last column of Table 3) do not seem to be influenced in their decisions by distance variables, perhaps because the influence of these variables was already exercised in the switch from the traditional system to the current system. However, a sizeable effect is measured on the performance of firms with H, albeit without a lot of precision.

5.3 Learning Curve

Table 4 presents the results of OLS estimations of performance measured as the firm's ROI 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.[21] The resulting learning curves—predicted profiles using these estimates—are illustrated in Figure 3. The coefficients associated with

[20] A more detailed look at the data, including information about the firm's location, age, size, in addition to industry, as we have done in column (6) of Table 2, was not feasible here (recall that we are controlling here for firms' current system).

[21] 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.

experience with T are not significant, and the learning curve is, of course, flat. The slope coefficients for the H 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 F are also significant at the 5% level. 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 H, 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 H profile stands above the others (hypothesis H1c).

5.4 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 H for the D and F after a minimum of accumulated experience, but not so for T. We find strong evidence of learning-by-doing effects for firms in the H system, consistent with the learning curve hypothesized in H1b; we do not find evidence of learning from experience for the T system, and for the F system we find that its adoption is associated with a decline in productivity. The latter finding suggests that organizational capabilities honed in predecessor systems (mostly T) do not help with running F. This is also consistent with H1a in that accumulated experience with F increases not only organizational capabilities but also the need to switch to a more balanced system. The results are also indicative of the importance of matching effects as stated in 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 H3b for the impact of the distance to the metropolitan center. There is some support for H3d and H3e related to the role of information on other firms' average performance by system; 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, as well as the small number of observations in each of the detailed cells.

5.5 Robustness Checks

5.5.1 Alternative Specification of Systems

Our characterization of organizational systems is based on a parsimonious and theoretically-driven approach. The financial incentives (F) and decision-making (D) systems we use cover a wide range of workplace practices, but exclude other practices such as TQM, training, job rotation, promotion from within and employment security These practices may be regarded as practices that support or complement allocation of decision-making and financial incentives and we group them into a third category of supporting practices (S) in a similar way to the construction of the D and F systems. This generates eight systems - T, D, F, S, D&F, D&S, F&S, D&F&S – instead of the four systems we used thus far.

We replicated the analysis in Table 2 with the eight systems (computing experience variables and system distribution, and average firm performance by system). We define the dependent variable as a switch to a more complex system for changes from: (a) T to any other system, (b) the single dimensional systems (D, F or S) to the two-dimensional ones (D&F, D&S, F&S) or to the three-dimensional system (D&F&S), and (c) the two-dimensional to the three-dimensional system.

The results, available upon request, are qualitatively similar for learning about the match and social learning based on networking but weaker for the effects based on variables interacted with systems (experience with a system and performance under a system). For learning-by-doing, the intermediate system S has a U-shaped effect on the likelihood of switching to a more complex system similar to the effect associated with experience with system F in Table 2; a similar but weaker effect is found for the D&S and F&S systems. The intermediate system D&F (H, but without supporting practices) has a strong positive linear effect on switching to a more complex system. For learning about the match, the effect is the same as in Table 2. For social learning based on system distribution, the proportion of firms in the financial incentives system significantly reduces the probability of switching to a more complex system and none of the other variables, including those on average performance by system in a firm's own industry, are significant.

5.5.2 Alternatives to the Learning Hypothesis

Our results may be interpreted without reference to learning. One possibility is that switching to a more complex system is due to an increase in the availability of relevant resources. We test for the resource availability hypothesis by testing the significance of the lag of firm performance in *levels* in the regression of equation (1), and testing whether the inclusion of performance in levels affects the estimated learning effects. The results, available upon request, show that lagged firm performance has no significant impact on switching decisions, and that controlling for it does not change the effects of the proxies for learning about the match, learning-by-doing and social learning.

Another possibility is that the differential adoption trends across systems observed in Figure 1 is pure firm heterogeneity and the variables we used to capture learning actually capture firm fixed effects. If this were so, the effects of these variables should disappear in fixed-effect estimations of equation (1). In fact, we find that the fixed-effects estimates of previous-period changes in performance, experience with the system and lagged average performance under system H (of firms in the firm's own industry) are similar or slightly larger in magnitude, with larger standard errors as compared to the OLS estimates. Due to the greater standard errors, previous-period change in performance is not significant in the fixed-effects estimations but experience with the system and lagged average performance under system H remain significant. Overall, the proxies for learning-by-doing and social learning effects are still important after controlling for firm heterogeneity.

There are complementary factors that also affect productivity and workplace organization, including computerization, production technology and business strategy (Bartel, Ichniowski and Shaw, 2005). Learning about organizational capabilities is also likely to affect the decision to complement the change in workplace organization with computerization and customized production strategies. The matching argument implicitly assumes that organizational capabilities are positively correlated with decisions of computerization and customized production (or that the benefits of the combination of computerization, customized production and the high-performance system are greater for higher-capability firms). Empirical testing of this claim requires longitudinal information on computerization, production technologies and business strategy decisions in addition to the firm's choice of system, which we do not have. However, the survey contains information about the level of complexity of core employees' tasks. 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 industry, unionization and firm size). This is consistent with the idea of a positive correlation between technology and workplace organization.

6. Conclusions

How do firms learn about what adjustments they need and can make in the organization structure of their workplace? Investigating changes that a sample of firms made in the allocation of decision-making rights and financial incentives during the 1980s and the first half of the 1990s, a period of transformation of the American workplace, we find that organizational learning 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 pattern of adjustments reflects discriminating use of private and public information as well as networking opportunities. Information about a firm's own performance matters most for switching out of the intermediate systems to 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 favorable performance signals, and on the average performance of firms that already have the high-performance system.

This two-stage progression of systems reveals 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 firms that have already the high-performance system. Caution in the face of uncertainty may be one reason for this pattern, but there are other factors that may contribute to it. In particular, mid-level management and some unions may resist change they regard as adverse to their interests, and future research should address its role in relation to learning.[22]

A natural extension of our analysis would be to estimate the comparative benefits of different learning mechanisms. We did compare performance outcomes of firms before and after a change of system and those who did not change systems at all and found that firms that remained under the traditional system throughout the period have flatter experience-performance profiles than firms that remained with the high-performance system, but our dataset did not allow estimation of learning curves *across* systems and firms to understand in detail the combined effects of the three learning mechanisms on performance. Future research should emphasize the performance dynamics of firms following different system adjustment paths.

[22] In our analyses we controlled for unionization status (estimates on control variables were not reported in the tables nor discussed in the text). Unionization has a positive impact on the likelihood of introduction of more complex organizational systems.

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Figure 1: The Evolution of Organizational Systems

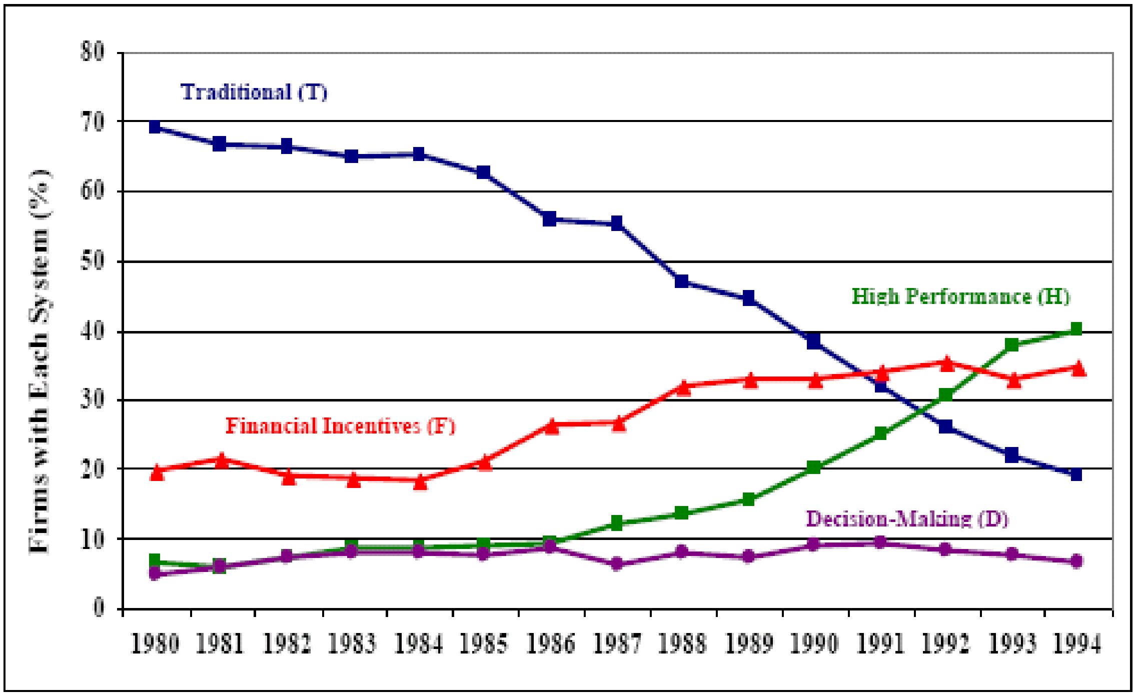


Figure 2: Classification of Organizational Systems

Complexity

		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

Table 1: Patterns of Change (Transitions) in Organizational 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 system at t-1; S_t is the system in t. Observations reflecting no change in 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	Mat-ching	Social learning					All learning mechanisms	
			Distance from		*System distribution and performance*				
			Minne-apolis	All other firms	Same Industry	Ind./age/ size/city[d]	Other Industry	Same Industry	Ind./age/ size/city[d]
	(1)	(2)	(3a)	(3b)	(4a)	(4b)	(4c)	(5a)	(5b)
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[d]									
Proportion in system F					**-0.122**	**-0.028**	**0.420**	**-0.071**	**-0.002**
					(0.282)	*(0.056)*	*(1.251)*	*(0.298)*	*(0.053)*
Proportion in system D					**-0.662**	**-0.107**	**2.838**	**-0.753***	**-0.103**
					(0.453)	*(0.092)*	*(1.743)*	*(0.426)*	*(0.113)*
Proportion in system H					**-0.193**	**-0.172**	**-0.418**	**-0.361**	**-0.128**
					(0.369)	*(0.192)*	*(1.320)*	*(0.376)*	*(0.091)*
Lagged average performance[d]									
Performance system T					**-0.081**	**-0.011**	**-0.206**	**-0.060**	**-0.009**
					(0.173)	*(0.050)*	*(0.201)*	*(0.160)*	*(0.047)*
Performance system F					**-0.138**	**-0.180*****	**0.032**	**-0.136**	**-0.155*****
					(0.138)	*(0.064)*	*(0.154)*	*(0.137)*	*(0.057)*
Performance system D					**-0.067**	**-0.065**	**0.191**	**-0.046**	**0.022**
					(0.091)	*(0.043)*	*(0.152)*	*(0.069)*	*(0.049)*
Performance system H					**0.340****	**0.271*****	**-0.112**	**0.328****	**0.233*****
					(0.155)	*(0.086)*	*(0.184)*	*(0.147)*	*(0.085)*
LR Chi2	38.42	34.16	30.81	28.27	49.02	52.07	23.61	79.05	67.79
(p-value)	(.000)	(.000)	(.000)	(.003)	(.000)	(.000)	(.130)	(.000)	(.003)

[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 for the nonlinear terms were computed following Ai and Norton (2003) using procedure 'predictnl' in Stata. Robust standard errors are in parentheses. ***= 1% level of significance. **=5% level of significance. *=10% level of significance. Number of observations is 631.

[b] Also includes union and industry dummies, cubic functions of lagged firm size, firm age (unless system experience is used), and year.

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

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

Table 3: Multinomial Estimation of the Choice of Organizational System

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
Learning By Doing			
Firm age[d]	**-0.003**	**0.003**	.
	(0.002)	*(0.003)*	
(Firm age)^2	**0.000**	**-0.000**	.
	(0.0000)	*(0.000)*	
Experience with system T	.	.	**-0.000**
			(0.002)
(Experience with system T)^2	.	.	**-0.0000**
			(0.0000)
Experience with system F	.	.	**-0.016***
			(0.005)
(Experience with system F)^2	.	.	**0.0023***
			(0.000)
Experience with system D	.	.	**-0.020**
			(0.014)
(Experience with system D)^2	.	.	**0.0042***
			(0.0005)
Matching			
Lagged relative performance[e] (Change)	**0.029**	**0.000**	**0.031***
	(0.021)	*(0.001)*	*(0.020)*
Social Learning			
Distance from Minneapolis (log)	**-0.017**	**0.001**	**-0.0024**
	(0.016)	*(0.002)*	*(0.011)*
Lagged system distribution[f]			
Proportion in system F	**-0.328**	**0.009**	**0.279**
	(0.381)	*(0.044)*	*(0.424)*
Proportion in system D	**-0.793**	**0.075**	**-0.037**
	(0.712)	*(0.103)*	*(0.739)*
Proportion in system H	**-0.253**	**-0.077**	**0.074**
	(0.671)	*(0.121)*	*(0.535)*
Lagged average performance[f]			
Performance system T	**0.171**	**-0.032**	**-0.094**
	(0.239)	*(0.041)*	*(0.164)*
Performance system F	**0.196**	**-0.049**	**-0.077**
	(0.335)	*(0.034)*	*(0.160)*
Performance system D	**-0.430**	**-0.015**	**-0.042**
	(0.277)	*(0.055)*	*(0.064)*
Performance system H	**0.065**	**0.115***	**0.285**
	(0.283)	(0.061)	*(0.218)*
LR Chi2	567.76		73.66
(p-value)	(0.000)		(0.000)
N	358		294

[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), and year. Marginal effects for the non linear terms were computed following Ai and Norton (2003) using procedure 'predictnl' in Stata. Robust standard errors are in parentheses. ***= 1% level of significance. **=5% level of significance. *=10% level of significance.

[d] Firm age is equivalent to experience with the traditional system for firms currently in system T.

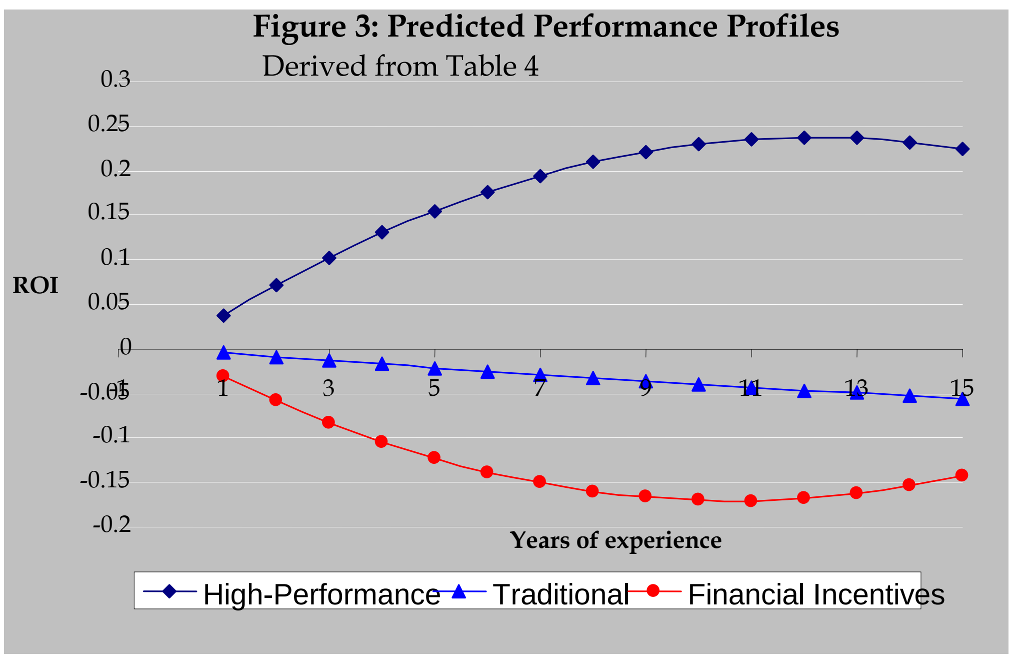
[e] Performance is measured using the firm's returns on investment, computed relative to average returns in the firm's industry.

[f] Distribution and average performance of firms in the firm·s own industry.

Table 4: Learning-by-Doing Effects[a]
Performance Dynamics by System

Dependent Variable: Return on Investment (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



[a] Only observations for firms that did not change systems, and post system change for firms that did change system. Observations before a system change are excluded because they reflect an abandoned system.
[b] All regressions include a union dummy, year dummies for 1980–1994, industry dummies, and firm size. Robust standard errors are in parentheses. ***= 1% level of significance. **=5% level of significance. *=10% level of significance.
[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 A: 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 A provides summary statistics for the sample with non-missing information on the ROI variable. 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 we dropped observations on firms in the high-performance system after a switch to that system throughout the remaining of the sample period and excluded firms that started with the high-performance system and kept it throughout the entire period. Given that for these firms there is no higher performance system to switch to, we drop them from the analysis ;the sample size drops to 631 observations. For the analyses in Table 3, the dataset is divided into the sample of firms with the traditional system (784 observations) and the sample of firms with either the decision-making system or financial incentives system (662 observations). For the matching analysis these two samples drop in size because we use the second lag of changes in the performance for ROI, so the final number of observations is 358.