Knowledge Sharing and Incentive Design in Production Environments: Theory and Evidence

Yuhchang Hwang*

David Erkens*

John H. Evans III++

November, 2006

*W. P. Carey School of Business, School of Accountancy
Arizona State University
PO Box 873606
Tempe, AZ 85287-3606
Hwangy@asu.edu
David.Erkens@asu.edu

++Katz Graduate School of Business, University of Pittsburgh
Pittsburgh, PA15260
jhe@katz.pitt.edu

Preliminary; please do not quote.

We thank seminar participants at Cornell University, the University of Pittsbugh and Arizona State University particularly Rob Bloomfield, Tom Dyckman, Vicky Hoffman, Donald Moser, Nandu Nagarajan, Bill Taylor, Sanjay Gupta, Michael Mikhail, Steve Kaplan, J. K. Aier, Rick Laux, Zhan Gao and especially Jason Schloetzer, for their helpful suggestions and comments.

Abstract

Knowledge Sharing and Incentive Design in Production Environments: Theory and Evidence

In this paper we develop and empirically test a parsimonious model of how specific knowledge and the value of knowledge sharing influence manufacturing plants' incentive design choices; i.e., the choice of input versus output performance measures and the relative incentive weight placed on individual versus group-based output performance measures. Our results confirm the prediction that increases in the depth of agents' specific knowledge and the value of knowledge sharing are associated with greater reliance on output performance measures. Similarly, consistent with previous research, we also find that the noisiness of output performance measures is negatively associated with their use. Finally, although increases in the value of knowledge sharing are associated with a greater incentive weight on group-based output performance measures, increases in the depth of agents' specific knowledge shift the incentive weight back towards individual-based output performance measures.

1. Introduction

Firms compensate employees in exchange for the services employees provide. Firms design compensation systems, and more broadly human resource systems, to attract and retain certain types of employees, and to give them incentive to provide the level and mix of services the firm prefers. Over the last 25 years, one response of U. S. manufacturing firms to increased competition has been to introduce new compensation policies for production employees (Fortune 1988, Milgrom and Roberts 1992). These new arrangements generally replace fixed hourly pay with variable compensation. An intriguing feature of these new arrangements, and the focus of our paper, is the surprising range of alternatives that firms use. The objective of our paper is to characterize optimal compensation arrangements in a parsimonious model, and to provide empirical evidence with respect to the resulting predictions.

We characterize modern compensation practices for production employees along two dimensions. First, pay can depend exclusively on employees' inputs or it can depend on both inputs and outputs (Lazear 2000a). Second, output measures can be either individual-based or group-based.[1] As developed in Raith (2005), the distinction between inputs and outputs to a firm's production function focuses on the observation that employees have greater control over inputs whereas outputs are also significantly influenced by exogenous state realizations. Typical input measures include the quantity and quality of employees' effort, as well as employees' behavior and knowledge, as reflected in personnel appraisals, skill certification and documented experience. Output measures include the quantity and quality of production, as well as associated financial measures such as expenses or profits.

Input measures are typically individual-based, while both individual-based and group-based output measures are common. Examples of individual-based output pay include individual piece rates paid to each employee based on that employee's own production. Group-based output pay arrangements include gain-sharing arrangements that pay bonuses when groups of production employees achieve budgeted cost targets.

Given the concerns with efficiency and quality common to all manufacturing plants, we find a surprisingly rich diversity in how the approximately 2,200 U.S. manufacturing plants in our sample compensate their employees. For instance, approximately 49% compensate production employees based on their outputs. Further, within this group, 32% uses exclusively individual-based output performance measures, 40% uses exclusively group-based output performance

[1] Alternatively, modern manufacturing compensation practices might be described along a variety of other dimensions, including job content and personal characteristics (Snell and Dean 1994), choice of performance standard; e.g., internal versus external performance standards (Murphy 2001) and divisional versus group performance measures (e.g., Bushman et al, 1995; Keating, 1996).

measures, and the remainder uses a combination of individual-based and group-based output performance measures.

The theme of our paper is that a significant portion of the preceding diversity in production employees' compensation can be explained by the extent of employees' specific knowledge and the potential value created when they share that knowledge with other production employees. In our production context we characterize this specific knowledge as information that pertains to production employees' decision-making but is difficult to communicate to management (Raith 2005, Prendergast 2002).[2]

Our focus on specific knowledge and the value of knowledge sharing to explain observed compensation arrangements contrasts with earlier agency literature that views incentive contracts primarily as responding to moral hazard over the level of employees' effort (Holmstrom 1979). More recent research (Holmstrom and Milgrom 1994, Prendergast 2002, Raith 2005) emphasizes that in many settings a more important concern than inducing enough effort is inducing the proper mix of efforts across tasks. The proper mix of efforts often depends on employees' specific knowledge of local production conditions. Compensation based exclusively on inputs cannot provide employees with incentive to use their specific knowledge, whereas compensation based on outputs provides this incentive by attaching greater rewards to greater production, lower cost, higher quality, etc. However, the cost to the firm of tying pay to outputs is that the employees must be compensated for the risk associated with the output measures. Therefore, assuming that management can observe production employees' effort levels, the firm must trade off the costs and benefits of tying compensation to outputs.

To address the role of specific knowledge and how it is shared in manufacturing environments, we extend Raith's model (2005) to incorporate multiple employees who each possess unique specific knowledge that they can share. We use the model to demonstrate how a plant's production technology and operating environment influence the optimal choices of performance measures and incentive bases. More specifically, to reflect the nature of the plant's technology, we vary the extent of employees' specific knowledge and the value of sharing that knowledge, while we represent changes in the plant's operating environment by the extent of exogenous output uncertainty the plant faces.

We first derive predictions from this model regarding the choice of output performance measures and the incentive weight placed on these performance measures as a function of the plant's technology and operating environment. We then test these predictions using data from the

---

[2] Specific knowledge is private information that is too costly to be communicated to management. In contrast, we assume that measures of employee knowledge and skills (e.g., certifications) are contractible.

IndustryWeek 2000 Annual Census of Manufacturers, a national survey of manufacturing plants. Our empirical tests are based on proxies for the plant's technology and operating environment, as well as controls for a variety of other plant characteristics.

This study makes three contributions to the literature on management control systems and incentive system design. First, we add to the growing literature on the role of specific knowledge in organizational design by showing how specific knowledge and the value of knowledge sharing influence the choice of performance measures and individual versus group-based incentives. Second, we extend previous empirical studies that investigate the choice of internal versus external performance standards (Murphy 2001) and divisional versus group performance measures (e.g., Bushman et al 1995, Keating 1997). We do so by examining the firm's choice of performance measures (input versus output) and incentive bases (individual versus group). We extend earlier results showing that noisier signals will be weighted less heavily in incentive arrangements (Banker and Datar 1989) by demonstrating how optimal incentives based on firm outputs become sharper when agents have better information about the state of the firm's production technology. Third, previous studies of incentive design practices have generally relied on relatively small samples (e.g. Bushman et al. 1995; Keating 1997) or have focused exclusively on one industry in order to control for technology (e.g. Ichniowski et al. 1997). In contrast, our sample of approximately 2,200 plants spans all the manufacturing 2-digit SIC codes.

Section 2 provides a review of the previous incentive design literature that is particularly relevant to our study. Section 3 develops a two- agent model in which both agents take observable actions and have specific knowledge they can share. Section 4 develops testable hypotheses based upon the predictions from the model in section 3. Finally, section 5 reports the results of our empirical tests and Section 6 presents a summary and conclusions.

2. Specific Knowledge, Choice of Performance Measures and Value of Knowledge Sharing

2.1 Specific Knowledge and Incentive Design

Previous literature stresses the potential value of assigning decision rights to agents who possess a high degree of specific knowledge. The more sensitive is the firm's production technology to local circumstances, such as the physical condition of various combinations of inputs, the more the firm depends on on-site production employees' specific knowledge in making production decisions.

Raith (2005) develops a two-task, single agent model in which the agent possesses specific knowledge on the productivity of each task, but finds it prohibitively expensive to communicate this information to the principal. The agent's efforts across two tasks, together with exogenous state uncertainty, determine the principal's total output. The agent's effort choices are observable and contractible, and the output to the principal is measured with noise.[3] By delegating decision rights over the mix of efforts across tasks to the agent and using output performance measures to determine the agent's compensation, the principal gives the agent incentive to utilize her specific knowledge to benefit the principal. Although output performance measures are typically noisier than input performance measures, the cost of this additional risk may be offset by the potential gains from exploiting the agent's specific knowledge. Therefore, in contrast to reducing the incentive weight on noisier signals in a pure moral hazard environment (Banker and Datar 1989), when agents have specific knowledge, the owner may prefer to contract on noisier output performance measures even when less noisy input performance measures are available.

Prendergast (2002) also demonstrates how equilibrium contracts may impose more risk on agents as the agents' specific knowledge increases. Prendergast (2002) argues that agents are likely to have more knowledge about which actions to take than the principal in environments characterized by uncertainty and a prohibitively high cost of communicating the agents' private information to the principal. Prendergast (2002) shows how the value of agents' private information can increase in more uncertain environments, and consequently how delegation and output performance measures can be observed more frequently in high risk environments. We next relate specific knowledge to the selection of input and output performance measures, and the relative incentive weight placed on individual-based versus group-based output performance measures.

2.2 Input versus Output Performance Measures

Input performance measures reflect the agent's input activities, while output performance measures reflect the subsequent results or outcomes of the agent's decisions and efforts. For instance, input performance measures could include the magnitude (e.g., hours) of the agent's effort, as well as the agent's associated knowledge and skills. Also, behavioral attributes such as tardiness, attitude, team orientation, etc. are also common input performance measures. In a manufacturing setting, input performance measures might include a machine operator's total production hours, the professional qualifications and certifications of the operator, the operator's total training time, and the operator's total experience operating the machinery.

[3] As discussed by Raith (2005, 8), assuming that inputs are measured perfectly is a convenient simplification of actual environments in which input measures are more generally noisy.

Output performance measures, such as the number of units produced, defect and yield rates, on-time deliveries, sales, profitability etc., reflect the combined influence of agents' decisions and related actions, as well as related uncontrollable factors. Manufacturing firms frequently base incentive pay on various financial and non-financial output performance measures, including productivity, yield and profitability measures. Such output performance measures are typically also critically dependent on factors beyond an agent's control, including the exogenous state of the economy and industry, climate conditions, government decisions, etc. Hence, in general, output performance measures are likely to be noisier measures of agents' actions than most input performance measures.

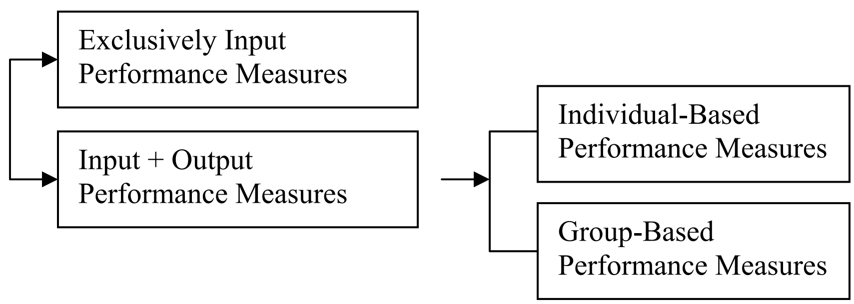
Anecdotal evidence and various case studies document that many firms employ a mix of input and output performance measures. For example, manufacturing firms including Nucor and Lincoln Electric use both behavior (input) and productivity (output) performance measures in evaluating their workers' performance (Govindarajan 2000, Nucor Mission Statement). These observations are consistent with the recommendations from the balanced scorecard literature that firms should employ a combination of both lead and lag indicators to guide and evaluate employees. In the balanced scorecard literature, learning and growth are common input performance measures, while sales, cost, and profit measures are typical output performance measures.

Manufacturing employees' specific knowledge with respect to materials and machinery has been described as "tribal" knowledge, and can be as subtle as shortcuts and other small innovations in operating the equipment, adjusting machinery, altering the production mix and production rate, etc. (Aeppel 2002). When manufacturing processes exhibit relatively little local variation (i.e., low specific knowledge) plants can rely on simple rules to prescribe the inputs that production employees are to provide. Consequently, when manufacturing tasks require only a modest amount of specific knowledge, plants will predominantly base compensation on inputs (i.e., whether rules have been followed). For instance, ServiceMaster is a company that provides commercial cleaning services and typically recruits employees with limited opportunities. The company's emphasis on the importance of input performance measures is legendary. Their annual report states that the company does not "fire people for lack of skill. We fire people for attitude problems."

In contrast, when the manufacturing process entails greater specific knowledge, simple input-based decision rules for production will typically no longer be adequate to guide employees to make optimal decisions. Instead, to motivate workers to use their specific knowledge in the firm's interest, owners should not only delegate considerable discretion to employees, but also evaluate employees on the resulting outputs (Raith 2005). Nevertheless, greater environmental uncertainty increases the cost to the firm of imposing output risk on production employees. Therefore, fixing the level of employee specific knowledge, as the environmental uncertainty facing the firm increases, the firm should respond by reducing the weights assigned to output performance measures.

2.3 Individual-Based versus Group-Based Measures

Incentive pay schemes with output based performance measures can be further characterized according to whether the measure reflects individual or group performance. Group-based input performance measures are less common because agents are generally not responsible for the behavior, skill, knowledge or effort of others. Conversely, both individual-based and group-based output performance measures are consistent with the notion that individual agents can influence both individual-based and group-based output measures:



Typical group-based measure and reward plans include gain sharing and pay based on line productivity and departmental defect rates. The size of a group or team can vary significantly, from a few individuals to all employees of a large firm.

Even when agents have limited decision-making discretion, the agency literature on moral hazard (Holmstrom 1982, Holmstrom and Milgrom 1994) establishes that group-based incentives can create valuable externalities. Group-based output measures can provide additional contracting information beyond that provided by individual-based performance measures. Group-based incentives can also be used to direct an agent's allocation of total effort toward tasks that benefits group performance but not necessarily individual performance.

For plants that tie compensation to output measures, specific knowledge plays an important role in how firms choose between individual-based and group-based compensation. Information sharing among production employees in a high specific knowledge environment is critical when pooled information produces significantly better production decisions. In turn, group-based pay may become optimal if it provides employees with the incentive to share considerable specific knowledge. For instance, the steel making process at Nucor Steel requires not only a high level of specific knowledge, but also substantial knowledge sharing to yield high quality products. Nucor believes that group incentives reinforce its knowledge sharing culture throughout the organization. At Nucor, "the bonus of a plant manager, a department manager's boss, depends on the entire corporation's return on equity. … At Nucor, we're not 'you guys' and 'us guys.' It's all of us guys. Wherever the bottleneck is, we go there, and everyone works on it" (Sloan Management Review 2000).

Scott and Tiessen (1999) investigate the incidence and importance of group-based performance measurement in managerial teams. Sprinkle and Williamson (2004) describe how increased competition led John Deere Corporation to alter their compensation and related human resource practices to encourage greater information sharing, cooperation and motivation among employees. They emphasize how the John Deere Corporation's shift from individual-based incentives with limited discretion to group-based incentives with significant discretion reflected management's intent to encourage production employees to use and share their considerable specific knowledge. Bushman et al. (1995) and Keating (1997) provide empirical evidence that when an agent's performance on individual tasks has spillover effects on group performance, the principal is more likely to employ group performance measures. More specifically, Bushman et al (1995) find that the use of aggregate or group performance measures in business unit managers' compensation contracts is an increasing function of divisional interdependencies. Keating (1997) demonstrates that these results continue to hold after controlling for growth opportunities and other performance measures (e.g. firm stock price).

Raith (2005) and Prendergast (2002) study the choice of input versus output performance measures. However, they do not address the influence of agents' specific knowledge on the choice of individual versus group-based incentives.[4] We extend Raith's analysis to explicitly incorporate how agents' specific knowledge is relevant to both individual and group tasks. Wruck and Jensen (1994) discuss how individual agents in quality teams possess valuable specific knowledge on productivity. However, the total potential value created by the quality team can be realized only when team members share their specific knowledge to improve production quality throughout the organization. The extensive interaction among production employees in modern manufacturing environments reflects the central importance of information sharing, organizational learning and empowered teamwork to firm performance (Wruck and Jensen 1994). The result is an intriguing challenge for the principal. How can the principal induce agents to

[4] Raith (2005) discusses how his model might explain the design of individual versus group-based incentive by reinterpreting inputs as measures of individual performance and outputs as measures of group performance. In contrast, our approach explicitly models knowledge sharing among multiple agents when each agent can choose how much effort to devote to individual and group tasks.

utilize their individual specific knowledge while simultaneously sharing it with their team? What are the proper incentive weights on individual-based versus group-based performance measures when information sharing is critical and agents possess extensive specific knowledge?

3. Model -- Choice of Performance Measure and Rewards

3.1 Theoretical Framework

In this section, we develop a parsimonious incentive contract model that highlights the most important insights of this paper. The objective of this model is to provide a framework for structuring and motivating our empirical analysis of the incentive design choices made at manufacturing plants. Consider a manufacturing setting in which the principal employs two workers. Each worker allocates her total effort (A_i) across two tasks – individual and group production.[5] Worker i devotes effort $a_i \in R^+$ to producing individual output (Y_i) and effort a_{iG} ε R^+ to producing joint output (Y_G).

Production: Total produced output Y is the sum of these two types of outputs: individual and group output, defined as $Y = \sum_i Y_i + Y_G$ where $i=1, 2$; and Y_i is individual output and Y_G is group output. Outputs Y_i and Y_G are either high (=1) or low (=0), as a function of the efforts (a_i, a_{iG}) and related productivity parameters, θ_i , θ_G. In particular, the probability of high individual output (Y_i=1) is $min\{a_i \theta_i ,1\}$, and the probability of high group output (Y_G=1) is $min\{(a_{iG} + a_{iG})\theta_G , 1\}$.

Production technology: The productivity of the plant's individual and group production technology is $\theta_i = \overline{\theta}\,(1+t\times\tau_i)$, $\theta_G = \overline{\theta}\,(1+ t\times\tau_G)$ where parameter τ_i , $\tau_G \in \{-1, 1\}$ are indicator variables (*High=1, Low=* -1) for productivity and $t \in [0, 1]$ is the variance of θ and reflects the firm's technological uncertainty. Each worker receives two private signals, $\{s_i,s_{iG}\}$, where s_i , $s_{iG} \in \{-1, 1\}$. We assume that workers cannot credibly communicate their private productivity signals to the principal (i.e. specific knowledge). The prior probability of high and low productivity is: $p(\tau =1) = p(\tau =-1) = ½$. Following Raith (2005), we define the following information structure for workers' individual tasks: $P(s|_i\tau_i)= P(\tau_i|s_i) =(1+\tau_i s_i k)/2$, where τ_i, $s_i \in \{-1, 1\}$. Parameter $k\in[0,1]$ represents the extent of workers' specific knowledge. As $k\rightarrow 1$ workers' specific knowledge becomes perfectly informative about the plant's production technology. As $k \rightarrow 0$, agents' specific knowledge becomes completely uninformative.

---

[5] An individual task could be the units produced on a machine the employee operates, while the group task could be the achievement of divisional budget targets for total production costs. Information sharing is likely to play a much more significant role in the group task than in the individual task.

For group production technology, we assume workers pool their private signals at no cost.[6] The information structure when workers pool their private signals is assumed to be: $p(s_{iG},s_{jG}|\tau_G)=(1+{}^1/_2\,(s_{iG}+s_{jG})\,\tau_G\,\rho\,k)/4$, where $\rho \in [1,1/k]$ and $s_{iG}, s_{jG} \in \{1 \text{ or } -1\}$. The information structure implies a posterior probability conditioned on pooling of private signals as $p(s_{iG},s_{jG}|\tau_G)=(1+{}^1/_2(s_{iG}+s_{jG})\,\tau_G\,\rho\,k)/2$ (see Appendix A for details). The coefficient ρ captures the value of knowledge sharing among workers. Note that as $\rho\rightarrow 1$, the group technology is identical to the individual technology where agents independently utilize their private signals (s_i, s_j). Conversely, as $\rho\rightarrow 1/k$, we have $p(\tau_G=1|s_{iG}=s_{jG}=1)=1$ and $p(\tau_G=1|s_{iG}=s_{jG}=-1)=0$. In this case, pooling information resolves all of the technological uncertainty.

Workers' Utility: Workers are risk-neutral and have utility w-$d(a)$, where w is compensation and the disutility of action is $d(a) = d(a_i^2+a_{iG}^2)$. Workers have limited liability, meaning that compensation cannot be negative. Each worker's compensation is linear in three contractible measures: $w(A_i) = \alpha+\beta(a_i+a_{iG})+\gamma_i+\gamma_G\,y_G$ where:

1. a_i ,and a_{iG} are input performance measures (i.e. efforts) with associated payment β. We assume that the principal has perfect information on workers' total effort.
2. y_i is the individual output performance measure with associated payment γ;
3. y_G is the group output performance measure with associated payment γ_G.

Assuming that the agent's participation constraint is not binding, we have α = 0 and agent i's utility function becomes:

$$U(A_i) = w(A_i) - d(A_i) = \beta(a_i + a_{iG}) + \gamma y_i + \gamma_G y_G - d(a_i^2 + a_{iG}^2) \qquad [1]$$

Performance Measurement: Output performance measures are related to the corresponding actual outputs through a common noise term $e\in[0,1]$. Specifically, the probability that $y_i=Y_i$ is $p(y_i=Y_i)=\frac{(2-e)}{2}$, where $e\in[0,1]$. Similarly, $p(y_G=Y_G)=\frac{(2-e)}{2}$. The common noise term "e" captures environmental uncertainty or measurement error associated with the output performance measures, both of which are beyond the agent's control.

Design Choices: In our model we made several design choices that are worth mentioning. First, in our model we focus on the influence of specific knowledge and sharing of this knowledge on incentive design choices. For simplicity and to avoid unnecessary distractions from the main focus of this paper we assume that the principal has perfect information on agents' input

[6] We assume that specific knowledge can be communicated among production workers at no cost, but is prohibitively costly to communicate to management. This assumed cost differential reflects the fact that specific knowledge is often related to production process related experience that resides at the local level.

measures (i.e. total effort is perfectly observable) but not on output measures. This assumption shifts the emphasis from the traditional moral hazard problem to a delegation problem in which agents have specific knowledge that is essential for productivity. Moreover, it is important to note that we assume that the principal has perfect information on workers' total delivered effort, but not on workers' effort allocation. We believe that this assumption will most adequately represent reality, because we believe that manufacturing workers are not likely to inform their supervisors of the exact time they spend collaborating with colleagues, but do report the total time they have worked in the manufacturing plant (e.g. time sheet). Second, for sake of brevity and simplicity we do not allow for other forms of incentives such as promotions.

Timing:

Principal chooses incentive weights	Agent receives private signals	Agent chooses effort levels	Productivity Parameter realized	Final outcomes and payoffs realized and reported
$\{\beta, \gamma, \gamma_G\}$	$\{s_i, s_{iG}\}$	$\{a_i, a_{iG}\}$	$\{\tau_i, \tau_{iG}\}$	$\{Y_i, Y_G, y_i, y_G\}$

Solving for optimal incentive contract: To solve for the optimal incentive contract we first solve for the agents' optimal effort levels. The expected value of individual performance measure y_i conditional on (θ_i, a_i) is:

$$\begin{aligned} E\left[y_i(\theta_i, a_i)\right] &= \sum\nolimits_{y_i} \sum\nolimits_{Y_i} y_i p\left[y_i \mid Y_i(\theta_i, a_i)\right] p[Y_i(\theta_i, a_i)] \\ &= \left(\frac{2-e}{2}\right) \times [\theta_i a_i] + \left(1 - \frac{2-e}{2}\right) \times [1 - \theta_i a_i] = \frac{e}{2} + (1-e) \times \theta_i \, a_i \end{aligned} \qquad [2]$$

Similarly, conditioned on the realization of efforts on group task, a_{iG} and a_{jG}, and the group productivity parameter $\theta_G \in [0,1]$, the expected value of y_G (i.e. group performance)is:

$$E\left[y_G(\theta_G, a_{iG}, a_{jG})\right] = \frac{e}{2} + (1-e) \times \theta_G \left(a_{iG} + a_{jG}\right) \qquad [3]$$

Hence, conditional on private signals (s_i, s_{iG}, s_{jG}), worker i's expected utility is:

$$E\left[U(a_i) \mid s_i, s_{iG}, s_{jG}\right] = \beta(a_i + a_{iG}) + \gamma\left[\frac{e}{2} + (1-e)\,\hat{\theta}_i a_i\right] + \gamma_G\left[\frac{e}{2} + (1-e)\,\hat{\theta}_G\left(a_{iG} + a_{jG}\right)\right] - d\,(a_i^2 + a_{iG}^2) \qquad [4]$$

Where $\hat{\theta}_i = E\left[\theta_i \mid s_i\right] = \overline{\theta}\left[1 + s_i tk\right]$ and $\hat{\theta}_{iG} = E(\theta_G \mid s_i s_j) = \overline{\theta}\left[1 + \left(\frac{s_{iG} + s_{jG}}{2}\right) 2tk\left(\frac{\rho}{1 + \rho^2 k^2}\right)\right]$ [5]

Consequently, the first-order conditions on worker *i's* effort level choices a_i^* and a_{iG}^* are:

$$a_i^* = \frac{\beta + \gamma(1-e)\hat{\theta}_i}{2d}; \quad a_{iG}^* = \frac{\beta_G + \gamma_G(1-e)\hat{\theta}_{iG}}{2d} \qquad [6]$$

Finally, we substitute the expected productivities [5] into equation [6] and substitute the resulting equation together with equations [2] and [3] into the principal's ex-ante profit function, take the expectations over the different realizations of the information signals and productivity parameters (s_i, s_j, s_{iG}, s_{jG}, π_i, π_j, π_G) and optimize. See appendix for details. This leads to the following optimal incentive weights:

$$\beta = \frac{(1-e)\,\bar{\theta}^2\left(k^2t^2\left(2+\rho^2(1+k^2t^2)\right)+1\right)+2\,d\,e\left(7+\left(3+2\rho^2\right)\right)k^2t^2}{2\,(1-e)\left(k^2t^2\left(7+4\rho^2(1+2k^2t^2)\right)-1\right)\bar{\theta}}$$

$$\gamma = \frac{(1-e)\,\bar{\theta}^2\left(k^2t^2\left(7+\rho^2(3+8k^2t^2)\right)-3\right)-d\,e\left(13+8\rho^2k^2t^2\right)}{2\,(1-e)^2\left(k^2t^2\left(7+4\rho^2(1+2k^2t^2)\right)-1\right)\bar{\theta}^2} \qquad [7]$$

$$\gamma_G = \frac{(1-e)\,\bar{\theta}^2\left(k^2t^2\left(1+\rho^2\left(1+2k^2t^2\right)\right)-1\right)-d\,e\,(5+4k^2\rho)^2}{(1-e)^2\left(k^2t^2\left(7+4\rho^2(1+2k^2t^2)\right)-1\right)\bar{\theta}^2}$$

3.2 *Model predictions:*

We first analyze the influence of *k*, the extent of manufacturing workers' specific knowledge, on the optimal incentive contract. More precisely, we derive the effect of *k* on the relative weight that the plants place on input versus output-based performance measures. All the proofs can be found in the appendix.

Proposition 1: As the depth of workers' specific knowledge (*k*) increases, the optimal weight on the input performance measure decreases ($\partial\beta/\partial k < 0$), whereas the optimal weights on the output performance measures increase ($\partial\gamma/\partial k > 0$ and $\partial\gamma_G/\partial k > 0$).

The above finding parallels Raith's (2005) result that, under the assumption of delegation, more specific knowledge calls for a greater weight on output performance measures. Therefore, even with perfect input performance measures, noisy output performance measures are advantageous because they induce workers to utilize their specific knowledge and thereby align workers' interests with that of the principal.

Next, we examine the effect of the potential value of knowledge sharing (ρ) on the optimal incentive weights placed on input versus output performance measures.

Proposition 2: As the value of knowledge sharing (ρ) increases, the weight on the input performance measure decreases ($\partial\beta/\partial\rho < 0$), while the weights on the output performance measures increase ($\partial\gamma/\partial\rho > 0$ and $\partial\gamma_G/\partial\rho > 0$).

Proposition 2 establishes that as the potential value of knowledge sharing (ρ)increases, the optimal incentive weight will shift away from input measures (i.e. decrease in β) towards output measures (i.e. increase in γ and γ_G). The increase in the incentive weight on group-based output (γ_G) follows directly because an increase in ρ means that the agents are now pooling more diagnostic signals. However, it is less intuitive why the optimal weight on individual output (γ) performance measures should increase. The intuition for this result follows from our assumption that the principal can only observe workers' total efforts and cannot observe the effort components related to the individual and group task separately. An increase in the value of knowledge sharing directly increases the returns to the group task, and produces a shift in the optimal incentive mix towards the group-based output performance measures (γ_G) and away from input performance measures (β). However, because the incentive weight on input performance measures is the same for effort on the individual and group task, a reduction in β would, ceteris paribus, also generate an indirect reduction in workers' efforts on their individual tasks. Therefore, to restore the workers' incentive to work on the individual task, the principal has to increase the weight on the individual-based output performance measures to compensate for the decrease in the input performance measures. Hence, an increase in the value of knowledge sharing results not only in greater incentive weight on group-based output performance measures, but also greater incentive weight on individual-based output performance measures. This leads to the interesting question of the **relative influence** of the potential value of knowledge sharing on individual versus group-based rewards, which we address next.

Proposition 3: $\frac{\partial\left(\gamma - y_G\right)}{\partial\rho} = \; < 0$ if $k^2t^2 > ¼$, For all $k, t > 0$ $\frac{\partial\left(\gamma - y_G\right)}{\partial k} = \; > 0$; and

$$\frac{\partial^2\gamma_G}{\partial\rho\,\partial k} < 0$$

Proposition 3 highlights an interesting result regarding the influence of specific knowledge (k) and the value of knowledge sharing (ρ) on the relative incentive weights placed on group (γ_G) versus individual-based output performance measures. When workers' specific knowledge is sufficiently high (i.e. i.e., $k^2t^2 > ¼$) the value of knowledge sharing among workers (ρ) has a stronger positive effect on the incentive weight placed on group-based rewards (γ_G) than on the incentive weight placed on individual-based rewards (γ). Although proposition 2 indicates that increases in specific knowledge results in a greater incentive weights on both the individual and group-based output performance measures; proposition 3 implies that the relative weight shifts from group to individual-based output performance measures when the level of specific knowledge increases.

Finally, proposition 3 shows that even though the value of knowledge sharing (ρ) leads to a shift in the weight from individual (γ) to group based output performance measures (γ_G) the influence of this effect is diminishing in the level of specific knowledge (k). Figure 1 in the Appendix depicts the above discussed relationships.

Finally, we examine the effect of performance measure quality, as reflected by e, the noisiness of the performance measure, on the relative weight placed on input versus output performance measures.

Proposition 4: As the quality of the output performance measure decreases or the overall environmental uncertainty increases (e increases), the weight on the input performance measure increases ($\partial\beta/\partial e > 0$); whereas, the weights on output performance measure decreases ($\partial\gamma/\partial e < 0$ and $\partial\gamma_G/\partial e < 0$).

The intuition for $\partial\beta/\partial e > 0$ is straight-forward and similar to findings from traditional agency models. Because input performance measures are presumed to be without noise, an increase in the noisiness of the output performance measure, leads to a shift towards input performance measures. As the variance (e) of the output performance measure (i.e. y) increases, the link between effort and performance weakens, and consequently incentives for agents to utilize their specific knowledge and to exert effort decreases.

4. Empirical Model

4.1 Sample Selection and Data Description

We obtain our data from the *4th Annual IndustryWeek Census of Manufacturers*, published in 2000. The plants surveyed had 2-digit SIC codes of 20-39, and an estimated employee population of at least 100 workers. The recipients of the survey held titles such as manufacturing manager and plant manager, and they reported on plant-level incentive features and other manufacturing practices. The raw database contained observations from 3,006 plants. Initial screening resulted in a loss of 840 or 28% of the observations due to incomplete information. The 2,166 sample plants reflect an industry distribution comparable to the

COMPUSTAT population, and cover all 2-digit manufacturing SIC codes with the most firms in fabricated metal, industrial and electronics (Table 1B).[7] Table 1A &1B contains descriptive statistics of our sample plants. Table 1C reports Average Size (Sales), Number of Employees and average plant age. The results indicate that the average plant is over 20 years old and employs over 200 employees. Approximately 45% of the sample plants experienced downsizing during the three years prior to the survey.

4.2 Translating Model Implications to Empirical Tests

We obtain our performance measure data from a survey item that asked respondents to list which forms of monetary rewards production employees receive. Our theoretical model makes predictions on the incentive weights placed on input measures, as well as individual-based and group-based output measures. Ideally, we would test the model's predictions using the specific incentive weights in employees' compensation contracts. However, because the survey does not report specific incentive weights, we base our empirical analysis on the relative likelihood that plants use specific types of performance measures (i.e., input versus input + output or individual versus group output measures).[8]

We assume that firms will only adopt specific performance measures when the economic significance of these performance measures outweighs the cost of implementation. Implicitly, it implies that the underlying optimal incentive weights must exceed a certain threshold. Thus, the same theoretical constructs that determine the incentive weights on performance measures in the model will also determine the likelihood of the actual usage of these performance measures by manufacturing plants. As an example, let γ^* denote the unobservable incentive weights on output performance measures (γ or γ_G) and z denote the threshold at which firms will implement individual and/or group based output performance measures. One can express the choice of a particular performance measures as follows:

$\gamma^* = X'\delta + \varepsilon$; $\Gamma = 1$ when $\gamma^* > z$; and $\Gamma = 0$ if $\gamma^* < z$.

Where

γ^* = the unobservable incentive weight placed on output performance measures;
Γ = binary variable that indicates the choice of a particular output performance measure;
z = threshold, $\gamma^* > z$ results in the actual adoption of the particular performance measure for a manufacturing plant's workers;
X = matrix of explanatory variables;

[7] As respondents report at the plant level and we do not have firm identifiers, it is possible that multiple manufacturing plants from one firm are included in the survey. Unfortunately, we have no means to control for this influence.

[8] By default all firms use some form of input performance measures. For instance all employers will evaluate their employees on their behavior for retention decisions.

δ = vector of coefficients.

Therefore, we translate our analytical predictions concerning incentive weights to corresponding predictions in terms of the probabilities that certain type of performance measures will be adopted.

Specifically, Proposition 1 implies that an increase in the level of specific knowledge results in a greater weight placed on output performance measures (individual-based and group-based). Translating this reasoning from incentive weights to the likelihood of incentive forms yields:

> **Hypothesis 1:** The greater the extent of specific knowledge required by the manufacturing environment, the more likely plants are to use output performance measures.

Hypothesis 1 implies that plants in manufacturing environments (e.g. production technology) requiring extensive specific knowledge are more likely to provide their workers with incentives to use this specific knowledge through output performance measures. The comparison is to plants with environments requiring far less specific knowledge. Similarly, Proposition 2 indicates that the weight on output-based performance measures increases as the value of information sharing among plant workers increases. Our second hypothesis again translates this result concerning incentive weights to a prediction concerning the likelihood of alternative performance measures:

> **Hypothesis 2:** For plants with manufacturing environments that require that workers possess at least a minimum level of specific knowledge, the greater the value of sharing this knowledge (i.e., the greater is ρ), the more likely plants are to use output performance measures.

Proposition 3 captures two aspects of the influence of knowledge sharing and specific knowledge on the relative incentive weight placed on individual and group-based output measures. First, while an increase in the value of knowledge sharing leads to a shift of the incentive weight towards group-based incentives, an increase in the level of specific knowledge leads to a shift in the incentive weight back towards individual-based incentives. Second, Proposition 3 also implies that knowledge sharing through teamwork is most productive when specific knowledge on how to solve a problem is dispersed throughout the organization. In particular, although the value of knowledge sharing leads to more weight on group-based pay, this effect is diminished as workers' specific knowledge increases. As noted earlier, because data on incentive weights is not available, we focus instead on the likelihood that plants will employ exclusively group-based output measures.

We assume that only when the perceived benefit of group-based output performance measures is relatively large compared to that of using individual-based output performance measures (i.e. $\gamma_G - \gamma$) plants will use exclusively group-based output measures. This assumption allows us to make clear inferences about the role of our theoretical constructs on incentive design when we restrict our sample to plants that use exclusively either individual or group-based output performance measures, but not both. The restricted sample allows us to perform contrast tests on the likelihood of choosing individual versus group-based output performance measures. We now reformulate the notions expressed in Proposition 3 in terms of predicted probabilities in Hypotheses 3a and 3b:

> **Hypothesis 3a:** Increases in the value of knowledge sharing (parameter ρ) increases the likelihood of using group-based output performance measures; whereas, increases in the level of specific knowledge (k) decreases the likelihood of using group-based output performance measures.

> **Hypothesis 3b:** Increases in the value of knowledge sharing (parameter ρ) increases the likelihood of using group-based output performance measures. However, as the level of specific knowledge increases (k), the influence of the value of knowledge sharing on the likelihood of using group-based output performance measures diminishes.

Finally, in a similar manner we develop Hypothesis 4:

> **Hypothesis 4:** As the uncertainty in a firm's operating environment increases, the likelihood that a firm uses output performance measures decreases.

4.3 Construction of Dependent Variable

As discussed above, the nature of our data requires us to analyze the likelihood of the choice of different types of performance measures -- input measures, as well as individual-based and group-based output measures rather than the corresponding incentive weights ; i.e., β, γ, γ_G. The survey asked respondents whether their plant offers the following monetary rewards to their production workers: (1) pay for knowledge, (2) pay for skills, (3) profit sharing, (4) gain sharing, (5) rewards for team performance, (6) rewards for individual performance, (7) other, and (8) no incentives.[9] We classified plants that they used (4) gain sharing, (5) rewards for team performance and/or (6) rewards for individual performance as using output measures

[9] Respondents were allowed to select multiple types of monetary rewards that apply.

(*OUTPUT*=1). Within this group, we further classify plants that use (4) gain sharing and/or (5) rewards for team performance as using group-based output measures ($\gamma_G=1$); and plants that select (6) rewards for individual performance as individual-based output measure ($\gamma=1$). It is important to note that plants that select exclusively item (4), (5) and/or (6) are not precluded to have some sort of "input-based" performance measure. It is impossible that promotions or pay raises are given without taking behavior, experiences or social criteria of an employee into consideration. Hence, we label the choice of output-based measures as input + output based performance measures.

Responses (1)-(3) are treated as input rather than output performance measures. Pay for knowledge and/or pay for skills (items 1 and 2) reward employees for their abilities to perform tasks rather than for the actual outcome of their productive efforts. Further, for several reasons, profit sharing is also not an ideal indicator of output based performance measure. First, profit sharing is often viewed by employees as an entitlement or as part of an employee benefit plan. Second, tax and pension planning considerations play a pivotal role in the use of profit sharing plans. In order to gain favorable tax treatment, the majority of the company-wide profit sharing plans are deferred. In these deferred plans, profits are credited to employees for distribution at retirement or some other future time period (Coats 1991).[10] Finally, the link between employees' performance and pay is at best weak as typically profit sharing plans allow the employer a significant amount of discretion over how and if contributions are made (Jackson et al. 2004). Further, the ambiguous responses given by firms that used other incentives (item 7) made this variable unreliable for use as an indicator of output incentives and finally, firms that provide their employees with no incentives (item 8) evidently do not provide their employees with output based incentives.

In sharp contrast to profit sharing plans, there are some general features of gain sharing plans that make them a good indicator of the type of group-based output performance measures included in our model in section 3.[11] First, gain sharing plans actively involve and stimulate employees to share their ideas via suggestion committees. Second, gain sharing plans usually involve all production workers and not only more senior workers, which is not always the case with profit sharing plans. Third, compared to profit sharing plans, gain sharing plans are relatively focused (e.g. plant, process), which makes it easier for employees to understand how

[10] In our sample, the distribution of the adoption of profit sharing plans is roughly equal across industries, while this is not the case for the other monetary reward forms. This finding further supports the notion that tax and pension planning considerations and not incentive considerations are the major reason for their implementation.
[11] For a detailed overview of the literature on profit sharing plans see Welbourne and Gomez-Mejia 1995.

they can contribute. Fourth, proceeds from gain sharing plans are usually paid out within a calendar year and are therefore not likely to be perceived as a pension benefit.

Finally, although the interpretation of rewards for team performance and individual performance is not well defined, the name of these reward types seems to be highly suggestive of the type of individual-based (i.e. γ) and group-based (i.e. γ_G) output performance measures that we modeled in section 3.

4.4 Explanatory Variables

As is the case with our dependent variable our survey dataset does not contain direct measures of our theoretical constructs of specific knowledge and knowledge sharing. However, our dataset does contain various plant characteristics that can potentially serve as reliable proxies for these constructs. For the choice of these proxies we rely on previous literature.

Specific Knowledge and the value of knowledge sharing. In our paper we define specific knowledge as information that pertains to production workers' decision-making and affects the firm's outcomes but is difficult to communicate to management (Raith 2005, Prendergast 2002). As mentioned above it is reasonable to assume that workers that operate in more complex production environments that exhibit a large degree of variation in local conditions will possess more valuable specific knowledge than workers that operate in simple and less variable operating environments. In a similar spirit the economics literature has investigated the link between manufacturing technology (i.e. manufacturing complexity) and workers' skill levels. An overwhelming body of empirical evidence has documented a positive association between the use of information technology (e.g. Kreuger 1993; Autor, Katz and Krueger 1996) and advanced production technology (e.g. Dunne and Schmitz 1995; Siegel 1995; Doms, Dunne and Troske 1997) and workers' skill levels. Hence, plants with more extensive investments in new production process technology and/or new information technology are likely to demand a significant degree of skills and knowledge from their workers. In contrast, low skilled labor such as an assembly line worker may not have much specific knowledge. Therefore, the intensity with which plants invest in information technology and production technology is an excellent proxy for the extent of workers' specific knowledge.

For our proxies for the value of knowledge sharing we turn to the characteristics of the plant's production environment and management initiatives. More specifically we use the commitment of the plant to initiatives that are related to total quality management and efficiency/speed of the production process as proxies for the value of knowledge sharing. Previous literature on TQM and JIT indicates that the critical common core practices for successful implementation of such initiatives requires employees' involvement, information sharing and feedback across the organization (Cua, McKone and Schroeder, 2001). Quality management initiatives require workers to not only develop their specific knowledge on a continuous basis, but also to share this knowledge with others (Wruck and Jensen 1994). Similarly, manufacturing initiatives that increase the efficiency and speed of the production process (e.g. agile manufacturing initiatives) require workers to share their knowledge with each other. Hence, the successful implementation of these initiatives requires a system approach to integrate these initiatives into production processes that are conducive to knowledge creation and dissemination. The integration of these procedures increases the potential gains of knowledge sharing among employees by providing an infrastructure for effective communication.

Given the discussion above, to identify proxies for specific knowledge and the value of knowledge sharing, we were especially interested in survey questions pertaining to 1) investments in information technology and new production equipment, 2) implementation of quality management initiatives, and 3) implementation of manufacturing initiatives that improve the efficiency and speed of production. We selected two set of survey questions in which respondents were explicitly asked to report to which extent they implemented initiatives related to these three categories. As many of the manufacturing initiatives reported in these two questions are likely to be correlated, we conduct simple factor analysis to reduce the dimensionality of the data. Table 2 contains the result of our factor analysis. Three factors emerged from the data. The first factor reflects the extent to which the plant implemented quality management initiatives (*QUALITY*). The second factor represents the plant's commitment to efficiency, speed (*SPEED*) and agility initiatives. Finally, the third factor reflects investment in new production and information technology. The factor is likely to be associated with the complexity of the plant's production environment and consequently the extent of specific knowledge. We therefore label this factor as *TECHNOLOGY*.

[Insert table 2 here]

To check the validity of the proposed proxy suggested by the factor analysis, Table 2b and 2C provide additional descriptive statistics. First, Table 2B relates the value of different levels of our knowledge sharing proxies (i.e. *QUALITY* and *SPEED*) with statistics on the extent of employee participation in self-directed teams, annual hours of formal training and annual labor turnover rate. Knowledge sharing is effective when decision rights are delegated to employees (self-directed team). Therefore, the greater the degree to which employees participate in self-directed teams, the more likely decision rights are delegated to them and hence the greater the value of knowledge sharing. Training is also viewed as an essential part of the knowledge sharing process. In addition a greater extent of knowledge sharing and empowerment creates a satisfying and fulfilling work environment which results in lower employee turnover. Consistent with the notion that our *QUALITY* and *SPEED* variables capture knowledge dissemination and sharing, we find that higher factor scores on *QUALITY* and *SPEED* are positively associated with training, employee participation in self-directed teams and negatively associated with the plant's labor turnover rate.

[Insert table 2b here]

Similar to how we validated our knowledge sharing proxies, Table 2c contains descriptive statistics on different levels of our specific knowledge proxy (*TECHNOLOGY*) with respect to the adoption of technology-based systems and the dollar value of shipments per employee. We found that plants with higher *TECHNOLOGY* factor scores are more likely to adopt advanced IT intensive technologies and have a higher value-added per employee. This provides additional evidence that our specific knowledge proxy is indeed capturing the complexity of the production environment and workers' skills and thus the extent of workers' specific knowledge.

[Insert Table 2C here]

Environmental Uncertainty. Our model predicts an inverse relationship between uncertainty in how effort and productivity are related to measured performance and the use of output performance measures. This measurement error (i.e. uncertainty) therefore stems from the underlying nature of the production process. It is easy to see how uncertainty in the production process concerning factors such as scheduling, inventory and maintenance can easily lead to increases in scrap rates, defect rates and warranty costs. Hence, the degree of environmental uncertainty is inversely related to a plant's first-pass quality yield rate[12]. We use the inverse rank[13] of this variable to proxy for environmental uncertainty (*UNCERTAINTY*). Consequently, higher values of this variable represent a higher degree of environmental uncertainty.

Control Variables. To control for the influence of other manufacturing practices unrelated to our theoretical constructs we control for how much progress the plant has made towards world-class manufacturing status (*MF PRACTICES*). Further, we attempt to control for product and general process characteristics by including the primary product order-fulfillment practice (*SPECIAL ORDER*), product mix (*MIX*) and production volume (*VOLUME*). Finally, we also include extent of unionization (*UNION*) and plant size (*SIZE*) as additional control variables.

[12] First-pass quality yield is the percentage of output that passes quality inspection as good prior to any rework.

[13] We ranked this variable to limit the influence of outliers. However, our results did not change when we used the unranked version of this variable.

Baron and Kreps (1999) discuss how firms with unions offer higher wages, rely more on seniority-based pay and have a different compensation mix, including a greater proportion of pension compensation. Given this evidence, we expect unionization to be negatively associated with incentive based pay in general. Plant size reflecting the facility's economy of scale, is also likely to be correlated with other management variables related to the choice of incentive design. Finally, previous studies have also found that the age and tenure of the workforce is negatively associated with the introduction of innovative work practices (Ichniowski and Shaw 1997, Ichniowski and Shaw 2003).

5. Empirical Results

The preceding hypotheses predict that increases in the depth of specific knowledge (Hypothesis 1) and the value of knowledge sharing (Hypothesis 2) are positively associated with the use of output-based performance measures. Hypothesis 4 predicts a negative relation between the extent of environmental uncertainty and the use of output performance measures.

Table 3 reports descriptive statistics on the frequency distribution of our sample plants' performance measures across key independent variables. The descriptive statistics are consistent with Hypotheses 1, 2 and 4 (see input + output column). The complexity of the production process (*TECHNOLOGY*), which proxies for the depth of workers' specific knowledge, quality initiatives (*QUALITY*) and (*SPEED*) which both proxy for the value of knowledge sharing, are all positively associated with the use of output-based performance measures. Similarly, greater environmental uncertainty (*UNCERTAINTY*) appears to be negatively associated with the use of output performance measures.

[Insert Table 3 here]

5.1 Testing Hypotheses 1, 2 and 4

Given that our choice variable (*OUTPUT*) is a binary variable, we use a logistic model to conduct our analysis. We use the following logit model to test the effect of specific knowledge, the value of knowledge sharing and environmental uncertainty on the choice of output performance measures (*OUTPUT*).

$$\begin{aligned} Logit(OUTPUT) = \alpha + &\beta_1\, TECHNOLOGY + \beta_2\, QUALITY + \beta_3\, SPEED + \beta_4\, UNCERTAINTY \\ &+ \beta_5\, MF\ PRACTICES + \beta_6\, ORDER + \beta_7\, MIX + \beta_8\, VOLUME \qquad [M1] \\ &+ \beta_9\, PROCESS + \beta_{10}\, UNION + \beta_{11}\, SIZE + \beta_{12}\, AGE + \varepsilon \end{aligned}$$

The logistic model results are reported in Table 4. Consistent with Hypothesis 1 and 2, we find that our extent of specific knowledge proxy (i.e. *TECHNOLOGY*) and our value of knowledge sharing proxies (i.e. *QUALITY* and *SPEED*) are all positively associated with the use of output-based performance measures. Further, consistent with Hypothesis 4 we find that our proxy for environmental uncertainty (*UNCERTAINTY*) is negatively and significantly associated with the use of output-based performance measures. Thus, overall the findings support Hypothesis 1, 2 and 4.

Finally, our coefficients on the extent of unionization (*UNION*) and Plant age (*AGE*) are negative and significant, indicating that plants with a greater extent of unionization and older plants are less likely to use output-based performance measures. Conversely, our proxy for plant size is positive and statistically significant. This implies that larger plants are more likely to choose output-based performance measures.

[Enter table 4 here]

5.2 Testing Hypothesis 3

Hypothesis 3 contains two predictions. First, in hypothesis 3a we predicted that increases in the value of knowledge sharing are *positively* associated with the likelihood of using group-based output performance measures (γ_G), while increases in the depth of workers' specific knowledge are *negatively* associated with the use of group-based output performance measures. Second, hypothesis 3b predicts that the influence of the value of knowledge sharing on the choice of group-based performance measures diminishes at higher levels of specific knowledge. Note that as mentioned in section 4.2, because of the lack of data on incentive weights we limit our sample to plants that use either individual or group-based output performance measures, but not both[14]. This results in a sub-sample of 753 observations.

Table 5 reports descriptive statistics on the frequency distribution of the use of individual and group-based performance measures across key independent variables. The descriptive statistics are consistent with Hypotheses 3a. Plants whose workers have a greater extent of specific knowledge are more likely to use individual-based output performance measures and less likely to use group-based output performance measures. Moreover, table 5 shows that higher levels of both our value of knowledge sharing proxies are associated with a lower probability of using individual-based output performance measures and a higher probability of using group-based performance measures.

[Insert table 5 here]

[14] We also conduct analysis by including samples which use both individual and group-based outcome performance measures. The results remain unchanged.

We use the following model to test the influence of specific knowledge and the value of knowledge sharing on the use of group-based (*GROUP*) output against individual output performance measures (Hypothesis 3a).

$$Logit(GROUP)=\alpha+\beta_1 TECHNOLOGY+ \beta_2 QUALITY+ \beta_3 SPEED+ \beta_4 UNCERTAINTY + \beta_5 MF\ PRACTICES+ \beta_6 ORDER+ \beta_7 MIX+ \beta_8 VOLUME + \beta_9 PROCESS+ \beta_{10} UNION+ \beta_{11} SIZE+ \beta_{12} AGE +\varepsilon \quad [M2]$$

[Insert Table 6 here]

Consistent with Hypothesis 3a (see Table 6), the extent of specific knowledge is negatively associated with the use of group-based output performance measures. This implies that it is more likely that manufacturing plants will move away from a group-based output performance measure to an individual-based output measure when the level of specific knowledge increases. Second, one of our knowledge sharing proxies is positive and significant (*QUALITY*), which indicates that as the value of knowledge sharing increases the likelihood of using group-based output performance measure increases. Further, although the sign of the coefficient on the other proxy for knowledge sharing (*SPEED*) is in the predicted direction, it is not significant at conventional significance levels. Therefore, in general, our findings support Hypothesis 3a.

To test Hypothesis 3b we add an interaction term between our specific knowledge proxy (*TECHNOLOGY*) and our value of knowledge sharing proxy (*QUALITY*)[15] to model M2. The results of this logit regression are reported in the second half of table 6. As table 6 shows, none of our main variables and also the interaction variable are significant at conventional significance levels. We attribute this lack of statistical significance to multicolinearity problems.

It is important to note that the coefficient on the interactive term of a logistic model does not reflect the overall "interactive" effect. As explained by Ai and Norton (2003), if one is interested in investigating the magnitude of an interactive effect in a nonlinear model one should not examine the marginal effect of the interaction term as this term can have the opposite sign and its statistical significance my be different as well. Therefore, to analyze the true magnitude of the interaction effect between the extent of specific knowledge and the value of knowledge sharing we use the procedure as described in Ai and Norton (2003).

Figure 2 contains the average interactive effect between specific knowledge and the value of knowledge sharing across different specific knowledge groups (ranked from highest to lowest). As the plot shows, there is a clear downward sloping pattern, which provides some credit to

[15] As we obtain similar results for the interaction between *TECHNOLOGY* and *SPEED* we only report one analysis and not both.

hypothesis 3b. However, we must note that when we calculated the statistical significance of the individual interactive effects, most of them were not significant at conventional significance levels.

Finally, our coefficients on progress toward world-class manufacturing (*MF PRACTICES*) and extent of unionization (*UNION*) are found to be positive and significant, indicating that plants with a high degree of unionization and plants that move more aggressively towards world-class manufacturing practices are more likely to use group-based output performance measures. Conversely, our coefficients on order fulfillment (ORDER) and plant age (AGE) are found to be negative and statistically significant at conventional significance levels. This implies that plants that have a greater portion of special orders and are older are less likely to use group-based output performance measures.

[Insert figure 2 here]

6. Discussion and Conclusions

We develop and test a parsimonious model relating specific knowledge, the value of knowledge sharing and environmental uncertainty to the firm's choice of output performance measures and the relative weight placed on individual versus group-based output performance measures. Our empirical results provide general support for the prediction that increases in agents' specific knowledge and the value of knowledge sharing are associated with a shift from exclusively-input performance measures toward a mix of input and output performance measures. More specifically, we find that after controlling for various manufacturing environment characteristics, the complexity of a firm's production technology (depth of specific knowledge) and the implementation of initiatives that improve the quality, speed and efficiency of the production process (value of knowledge sharing) are positively associated with the adoption of output performance measures. Next, the model predicts that when firms use output performance measures the level of specific knowledge is negatively associated with the use of group-based performance measures and the impact of knowledge sharing is positively associated with their use. Consistent with this prediction, we find a negative association between the level of workers' specific knowledge and the use of group-based output performance measures and a positive association between the use of these performance measures and the value of knowledge sharing. Moreover, we find some evidence that the influence of knowledge sharing on the use of group-based output performance measures is diminishing in the level of workers' specific knowledge. Further, similar to traditional agency models, our model predicts that the noisier output performance measures are, the less likely they are to be used. We find strong evidence for a negative relationship between environmental uncertainty and the use of output-based performance measures.

Our study has important implications for understanding the influence of specific knowledge on incentive design. In the context of delegation, previous studies such as Raith (2005) and Prendergast (2002) have focused on the choice of performance measures without examining the choice between individual and group-based output performance measures. To generalize the analysis to also address the important trade-off between individual and group-based performance measures, our model explicitly incorporates both the performance measurement and incentive base choices. The model underscores the point that performance measure and incentive base choices, although distinct, are ultimately related in a fundamental manner such that they should ideally be examined together.

In addition, this study contributes to the empirical literature on the determinants of performance measure choice. Previous empirical studies have predominantly focused on the informativeness of the information signal (e.g. Murphy 2001, Bushman et al 1995, Keating 1997). Our study complements such previous empirical work in two important ways. First, as discussed above, even when input performance measures are less noisy than output performance measures, it is optimal for the principal to reward agents based on their output when agents possess specific knowledge on the productivity of their tasks. Therefore, this study contributes to the empirical incentives literature by examining the influence of specific knowledge on firm's performance measure and incentive base choices, an aspect of incentive design that previously has received less attention. Second, as noted above, this study contributes to the empirical literature by examining the choice of performance measures and incentive base in a single unified framework. The simultaneous analysis of performance measure and incentive base choices permits a more comprehensive analysis of the complex incentive design choices that firms make.

Our results are subject to several limitations. First, our sample is restricted to firms that participated in the IndustryWeek 2000 annual census of manufacturers. As such, our results may not generalize to all manufacturing plants. Second, our data stems from archival survey data collected by a third party. Consequently, the survey questions were not designed for our specific hypotheses and hence our proxies can only imperfectly capture the underlying constructs. Finally, data on the implementation of manufacturing practices is self-reported, which could potentially bias our findings.

References

Aeppel, T., (2002). “On Factory Floors, Top Workers Hide Know-How from Managers.” *Wall Street Journal*, June 1.

Autor, David, Lawrence Katz, and Alan Krueger. 1998. Computing inequality: Have computers changed the labor market? *Quarterly Journal of Economics* 113 (November): 1169–1214.

Banker, R., Datar, S., (1989). “Sensitivity, precision and Linear Aggregation of Signals for Performance Evaluation,” *Journal of Accounting Research,* Spring.

Baron, J. N. & Kreps, D.M. (1999). Strategic human resources: Frameworks for general managers. New York: John Wiley & Sons.

Bushman, R., Indjejikian, R., Smith, A., (1995). Aggregate performance measurement in business unit compensation: the role of intrafirm interdependencies. *Journal of Accounting Research*, 33 (Suppl.), 101–128.

Coates, III, E. M. (1994), “Profit Sharing Today: Plans and Provisions”, *Monthly Labor Review*, Vol. 113 (4)

Cua, K. O., McKone, K. E. and Schroeder, R. G. 2001 ’Relationships between Implementation of TQM, JIT, and TPM and Manufacturing Performance’, *Journal of Operations Management* 19: 675-694.

Doms, Mark, Timothy Dunne, and Kenneth Troske. 1997. Workers, wages, and technology. *Quarterly Journal of Economics* 112 (February): 253–90.

Dunne, Timothy, and James Schmitz, J., “Wages, Employment Structure and Employer-Size Wage Premia: Their Relationship to Advanced-Technology and Jobs: Secular Change and Cyclical Dynamics,” NBER Working Paper No. 5656, July 1996.

Govindarajan, V.. “Nucor Corporation (A).” Tuck School of Business, Center for global Leadership. 2000

Holmstrom, B. (1979) “Moral Hazard and Observability.” *The Bell Journal of Economics,* Vol. 10, Issue 1(Spring,), pp. 74-91

Holmstrom, B. (1982) "Moral Hazard in Teams." *Bell Journal of Economics*. Vol. 13, pp. 324-340.

Holmstrom, B. and P. Milgrom (1994). “The Firm as an Incentive System.” *American Economic Review*, 84 (4, September): 972-991.

Ichniowski, C., Shaw, K., Prennushi, G., (1997). The effects of human resource management practices on productivity: a study of steel finishing lines. *American Economic Review*, 87 (3), 291–313.

Ichniowski, C., K. Shaw. (2003). “Beyond incentive pay: Insiders’ estimates of the value of complementary human resource management practices.” *Journal of Economic Perspectives*. 17 155–180.

Jackson, SB. Mauldin, EG, Wilcox, WE. and DL Kruse. (2004) “The effect of corporate restructuring charges on employer contributions to profit sharing plans”, J*ournal of Accounting and Public Policy*, Vol 23, 4.

Keating, S. (1997). “Determinants of divisional performance evaluation practices.” *Journal of Accounting and Economics* 24, 243–273.

Krueger, Alan. 1993. How computers changed the wage structure: Evidence from microdata, 1984–89. *Quarterly Journal of Economics* 108 (February): 33–60.

Lazear, E. P. (Dec. 2000). “The Power of Incentive.” *The American Economic Review*, Vol 90 No 2, 410-414.

__________ (May. 2000). “Incentive and Productivity.” *The American Economic Review*, Vol 90 No 5, 1346-1361.

Murphy, K. (2001). Performance measures in incentive contracts. *Journal of Accounting and Economics*, 30, 245-278.

Ai C, Norton EC. Interaction terms in logit and probit models. *Econ Lett*. 2003;80:123–129.

Prendergast, C. “The Tenuous Trade-Off between Risk and Incentives.” *Journal of Political Economy*. vol. 10, no.5, 2002:1071-1102

Raith M. “ Specific Knowledge and Performance Measurement.” Discussion Paper Series, No. 4262, Center for Economic Policy Research

Scott, T., Tiessen, P., 1999. Performance measurement and managerial teams. Accounting, Organizations and Society 24, 263-285.

Siegel, D. 1998. The impact of technological change on employment and wages: Evidence from a firm-level survey of Long Island manufacturers. Economics of Innovation and New Technology 5(2): 227-46.

Snell, S. and J. Dean. (1994). Strategic Compensation for Integrated Manufacturing: The Moderating Effects of Jobs and Organizational Inertia *Academy of Management Journal*, Vol. 37, No. 5 (Oct., 1994), pp. 1109-1140

Sprinkle, G. and M. Williamson, “The Evolution from Taylorism to Employee Gain Sharing: A Case Study Examining John Deere’s Continuous Improvement Pay Plan.” *Issues in Accounting Education. Volume 19, No. 4, 2004: 487-503.*

Wruck, K., Jensen, M., (1994). Science, specific knowledge, and total quality management. *Journal of Accounting and Economics* 18, 247–287.

Appendix :

Assumed Group Task Information Structure:

Consider the following general form of information structure, where $p(\tau_G = -1) = p(\tau_G = 1) = 1/2$ and $0 < m < 1$:

(s_{iG}, s_{Gj})	$p(s_{iG}\, s_{jG} \mid \tau_{G=1})$	$p(s_{iG}\, s_{jG} \mid \tau_G = -1)$
$(1,\ 1)$	$(1-2m+k\rho)/4$	$(1-2m-k\rho)/4$
$(1, -1)$	M	M
$(-1,\ 1)$	M	M
$(-1, -1)$	$(1-2m-k\rho)/4$	$(1-2m+k\rho)/4$

Based on the distribution of $p(s_{iG,}\, s_{jG} | \tau_G)$ defined above, the corresponding conditional probability of $p(\tau_G | \, s_{iG}\, s_{jG}) = \dfrac{p(\tau_G)p(s \mid \tau_G)}{\sum_G p(\tau_G)p(s \mid \tau_G)}$ can be expressed as :

$$p(\tau_G \mid s_{iG}, s_{jG}) = \frac{\left(1+\tau_G(s_{iG}+s_{jG})/2\right)\left(1-\tau_G(s_{iG}+s_{jG})/2\right)}{\left(1+\tau_G\left[\tau_G(s_{iG}+s_{jG})/2\right]^2 \rho\, k\right)^2 + \left(1-\tau_G\left[\tau_G(s_{iG}+s_{jG})/2\right]^2 \rho\, k\right)^2}$$

Denote $\hat{\theta}_G(s_{iG}, s_{jG})$ as the expected value of θ_G (the productivity parameter of the group task) conditional on workers' pooled private signals (s_{ig}, s_{jG}). The above defined information structure implies:

$$\hat{\theta}_{iG} = E(\theta_G \mid s_i s_j) = \bar{\theta}\left[1 + \left(\frac{s_{iG}+s_{jG}}{2}\right) 2t\,k\left(\frac{\rho}{1+\rho^2 k^2}\right)\right]$$

Derivation of Workers' Expected Payoff and Principal's Expected Profit Function

Next, we can express the unconditional expected values of the output performance measures as a function of the conditional mean of the underlying productivity parameters and the workers' corresponding private signals.

Denoting θ= $\{\theta_i, \theta_j, \theta_G\}$, the principal's ex-ante expected profit function becomes:

$$\begin{aligned} E(\pi) \quad &= E_I\left(\left(1-\gamma(1-e)\right)\times\left[\theta_i a_i + \theta_j a_j\right]\right) + E_I\left[\left(1-2\gamma_G(1-e)\right)\times\left(\theta_G(a_{iG}+a_{jG})\right)\right] \\ &\quad - E_I\left[\beta\left(a_i + a_j\right) + \beta\left(a_{iG}+a_{jG}\right)\right] - e(\gamma+\gamma_G); \end{aligned} \qquad [9]$$

where $\quad I = \{s_i, s_i, s_{Gi}, s_{Gi}, \tau_i, \tau_i, \tau_G\}$

Next, we substitute [5] into equation [6]. Then, we substitute both the resulting equation and equation [3] into the ex-ante expected profit function [9] and evaluate the expected values of equation [9] over the workers' signals(τ_i, τ_G,s_i,s_{iG}). One obtains the expected value of the resulting expression by taking 128 permutations (all signals have two possible values: +1, or -1) over possible combinations of signals (i.e. s_i,s_j,s_{iG} and s_{jG}) and production technology parameters (i.e. τ_i,τ_j and τ_G). Each permutation is then weighed by its corresponding probability:

$$\frac{(1+k\tau_i s_i)\times(1+k\tau_j s_j)\times\left(1+\left((s_{iG}+s_{jG})/2\right)\times\tau_G\rho k\right)}{128}$$

The above leads to the following expression of the principal's expected profit:

$$E\pi=\begin{pmatrix}\left(\frac{1}{d}\right)(1-(1-e)\gamma)\left(b+(1-e)\gamma(1+k^2t^2)\right)\bar{\theta}^2+\left(\frac{1}{2d}\right)(1-2(1-e)\gamma_G)\left(2b+(1-e)\gamma_G(2+\rho^2k^2t^2)\right)\bar{\theta}^2\\ -\beta\left(\frac{b+(1-e)\gamma\bar{\theta}}{d}\right)-\beta\left(\frac{b+(1-e)\gamma_G\bar{\theta}}{d}\right)-e(\gamma+\gamma_G)\end{pmatrix}$$

Proof of Proposition 1:

$$\frac{\partial\beta}{\partial k}=\frac{-1}{2(1-e)\ \left[k^2t^2\left(7+4\rho^2(1+2k^2t^2\right)-1\right]^2\bar{\theta}}$$
$$\left((1-e)\bar{\theta}^2\left[16+\rho^2\left(9+34k^2t^2\right)+\left(9+4\rho^2\right)k^4t^4\right]+4de\left(26+\rho^2\left[15+56k^2t^2+4\left(3+2\rho^2\right)k^4t^4\right]\right)\right)k\ t^2<0$$

Similarly, we have $\frac{\partial\gamma}{\partial k}>0$ and $\frac{\partial\gamma_G}{\partial k}>0$.

Proof of proposition 2:

We have:

$$\frac{\partial\beta}{\partial\rho}=\frac{-3\rho\ k^2t^2\left(3(1-e)\bar{\theta}^2\left(1+k^2t^2\right)^2+4de\left(5+4k^2t^2\right)\left(1+k^2t^2\right)\right)}{(1-e)\ \left[k^2t^2\left(7+4\rho^2(1+2k^2t^2\right)-1\right]^2\bar{\theta}}<0$$

$$\frac{\partial\gamma}{\partial\rho}=\frac{3\rho\ k^2t^2\left(3(1-e)\bar{\theta}^2\left(1+k^2t^2\right)^2+4de\left(5+4k^2t^2\right)\right)}{(1-e)\ \left[k^2t^2\left(7+4\rho^2(1+2k^2t^2\right)-1\right]^2\bar{\theta}}>0$$

$$\frac{\partial\gamma_G}{\partial\rho}=\frac{2\rho\ k^2t^2\left(1+2k^2t^2\right)\left(3(1-e)\bar{\theta}^2\left(1+k^2t^2\right)^2+4de\left(5+4k^2t^2\right)\right)}{(1-e)\ \left[k^2t^2\left(7+4\rho^2(1+2k^2t^2\right)-1\right]^2\bar{\theta}}>0$$

Proof of Proposition 3:

It is straight forward to show that $\frac{\partial(\gamma-y_G)}{\partial k}=\ >0$ and $\frac{\partial(\gamma-y_G)}{\partial k}=\ >0$ and

$$\frac{\partial\ (\gamma-y_G)}{\partial\rho}=-\frac{3(1-e)\bar{\theta}^2\left(1+k^2t^2\right)^2+\rho k^2t^2\left(4k^2t^2-1\right)}{(1-e)\ \left[k^2t^2\left(7+4\rho^2(1+2k^2t^2\right)-1\right]^2\bar{\theta}}<0$$

Furthermore, by taking the cross partial derivatives of the difference between the incentive weight placed on individual and group-based output performance measures over the value of information sharing and specific knowledge, we have $\frac{\partial^2 (\gamma - y_G)}{\partial \rho \, \partial k} = \; < \; 0$.

Proof of Proposition 4:

It is easy to show that $\partial\beta/\partial e>0$. By taking the first-order derivative of γ with respect to *e:*

$$\frac{\partial \gamma}{\partial e} = -\frac{d(1+e)\left(8(c+k)^2 t^2 + 13\right) - \overline{\theta}^2 (1-e)\left[k^2 t^2\left(7+\rho^2\left(3+8k^2t^2\right)\right) - 3\right]}{2(1-e)^3\left[\left(7k^2+4(c+k)^2\right)t^2 + 8(c+k)^2 k^2 t^4 - 1\right]\overline{\theta}^2} \qquad [10]$$

The sign of $\partial\gamma/\partial e$ is determined by the numerator term. The ex-ante expected value of the performance measure can be expressed as follows: $E(y_i)=(de+(1-e)(1+k^2)\overline{\theta}^2)/4d$. Consequently the derivative of $E(y_i)$ with respect to the noisiness of the signal ("*e*") can be expressed as: $\partial E(y_i)/\partial e = (d-(1+k^2)\overline{\theta}^2)/4d$. Note that $\partial E(y_i)/\partial e \geq 0$ implies $d \geq (1+k^2)\overline{\theta}^2$. Substituting this condition back into equation [10], it can be shown that the numerator of equation [10] > 0. Thus, we have $\partial\gamma/\partial e<0$. Applying similar reasoning to γ_G completes the remaining part of the proof.

The necessary condition for $\partial\gamma/\partial e<0$ requires $\partial E(y_i)/\partial e>0$. Unlike in traditional agency models, in our model changes in the variance of the signals affects the ex-ante unconditional mean of the signal. Other things equal, increases in $E(y_i)$ result in decreases in γ. More interestingly, even if we adhere to the traditional assumption of $\partial E(y_i)/\partial e=0$, an increase in *e* still unambiguously leads to a decrease in γ.

Figure 1: The Relative Weights on Individual versus Group Based

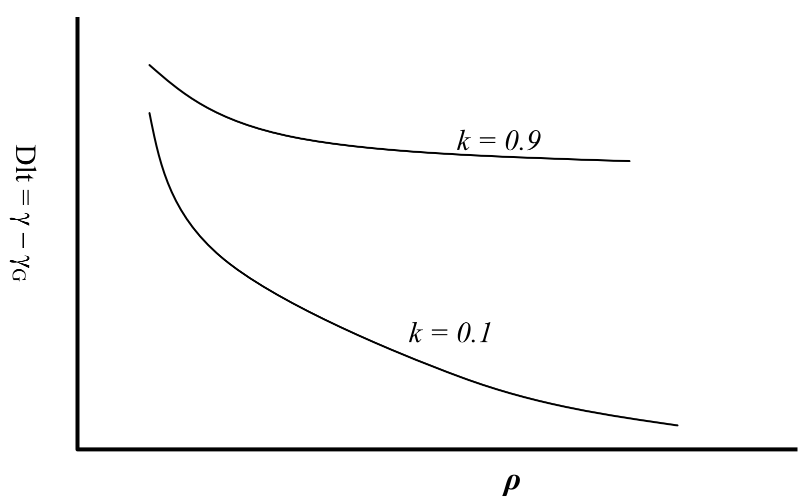


Table 1: Sample Distribution: Choice of Performance Measures

Total Sample (2,111 plants)

- Input-based — 1,126 (50.97%)
- Input + Output-based — 1,057 (49.03%)
  - Group Output — 428 (19.61%)
  - Group + individual Output — 298 (13.65%)
  - Individual Output — 331 (15.60%)

Table 1B: Sample Plants Distribution – by Industry

SIC Code	Industry	Count	Percentage
20	Food And Kindred Products	96	4.4
21	Tobacco Products	3	0.14
22	Textile Mill Products	60	2.75
23	Apparel And Other Finished Products Made From	23	1.05
24	Lumber And Wood Products, Except Furniture	52	2.38
25	Furniture And Fixtures	43	1.97
26	Paper And Allied Products	95	4.35
27	Printing, Publishing, And Allied Industries	50	2.29
28	Chemicals And Allied Products	124	5.68
29	Petroleum Refining And Related Industries	8	0.37
30	Rubber And Miscellaneous Plastics Products	161	7.38
31	Leather And Leather Products	9	0.41
32	Stone, Clay, Glass, And Concrete Products	51	2.34
33	Primary Metal Industries	125	5.73
34	Fabricated Metal Products, Except Machinery A	309	14.16
35	Industrial And Commercial Machinery And Computer	346	15.86
36	Electronic And Other Electrical Equipment And	290	13.29
37	Transportation Equipment	135	6.19
38	Measuring, Analyzing, And Controlling Instrument	140	6.42
39	Miscellaneous Manufacturing Industries	61	2.8
N		2,181*	

*Two observations have missing SIC codes. Our sample covers all industries in manufacturing sector.

Table 1c: Descriptive Statistics (% in parenthesis):

Age of manufacturing plant	< 5 years	5-10 years	11-20 years	20 years	
	90 (4.16)	171 (7.89)	404 (18.65)	1501 (69.30)	
Full-time employees	< 100	100-249	250-499	500-999	> 1000
	314 (14.38)	1073 (49.15)	487 (22.31)	202 (9.25)	107 (4.90)
Sales of parent corp. (Million)	No corporate parent	> 100	100-499	500-999	> 1 billion
	477 (22.66)	351 (16.67)	395 (18.76)	188 (8.93)	693 (32.97)
Downsizing during the past 3 years	No downsizing	Some downsizing	Significant downsizing		
	1167 (53.53)	757 (34.72)	256 (11.74)		

Table 2: Factor Analysis of Manufacturing/Quality Related Initiatives

	Factor 1: Knowledge Sharing (Quality Management)	**Factor 2:** Knowledge Sharing (Speed)	**Factor 3:** Extent of Specific Knowledge (Technology)
Formal continuous-improvement program	0.**6015**	0.3343	0.1521
Reengineered production processes	0.1830	**0.5452**	0.3028
Self-director or empowered work teams	0.3659	**0.5827**	-0.0720
Flexible, cross-functional workforce	0.0781	**0.6686**	-0.0275
Cycle-time reductions	0.2312	**0.5326**	0.2146
New process equipment / technologies	0.1809	0.1479	**0.6507**
New information technologies	0.1079	0.0732	**0.7777**
Supply-chain optimization	0.1752	**0.4658**	0.3914
Planning and scheduling strategies	0.0980	**0.4342**	0.4225
Agile manufacturing strategies	0.0565	**0.6418**	0.3173
Quality management programs	**0.6074**	0.1588	0.2697
Six Sigma	**0.5972**	-0.0069	0.0833
Total Quality Management	**0.7199**	0.1805	0.1484
Employee problem-solving teams	**0.6124**	0.3814	-0.0081
Error proofing (poka-yoke)	**0.4899**	0.2661	-0.0213
Statistical process control (SPC)	**0.7031**	0.0147	0.1974
Eigenvalue	**4.934**	**1.418**	**1.044**

Respondents were asked to rate on a 3-point scale to what extent they implemented the above initiatives (no implementation, some implementation and extensive implementation). The factor loadings reveal (highest factor loadings) that factor 1 is a quality management factor, factor 2 is an SPEED factor and factor 3 is a technology factor.

Table 2b: Factor 1 , 2 And Self-Directed Team, Training And Annual Labor Turnover Rate

	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
	Ranked by Factor 1: Quality Related Initiatives				
% worker participate in self-direct teams	13.74	18.14	24.23	29.68	40.33
Annual of formal training (Hours)	12.27	14.92	17.56	19.95	23.54
Annual labor turnover rate (%)	10.10	9.94	8.91	8.65	7.43
	Ranked by Factor 2: Speed/efficiency Initiatives				
% worker participate in self-direct teams	9.46	15.21	24.13	29.78	47.66
Annual of formal training (Hours)	13.50	15.74	18.33	18.37	22.31
Annual labor turnover rate (%)	9.78	9.30	9.01	8.78	8.17

Table 2c: Factor 3, Adoption Of Technology-Based System And Dollar Value Shipment Per Employee:

	Ranked by Factor3: Technology Related Initiatives				
	1st quintile	2nd quintile	3rd quintile	4th quintile	5th quintile
Bar coding (% of sample plants implemented)	36.49	42.98	44.68	48.10	61.14
Computer aid design (% implemented)	63.03	70.14	69.03	71.56	79.38
Computer integrated manufacturing (% implemented)	20.85	26.30	33.81	36.08	47.63
Computerized maintenance management (% implemented)	27.01	34.12	36.17	36.49	42.18
Dollar value shipment per plant employee (Thousand)	234.62	261.73	277.18	292.25	319.18

Table 3: Descriptive Statistics –Performance Measures, Specific Knowledge, Knowledge Sharing and Uncertainty

		Input versus Input + Output based Measures		
		Exclusively-Input Based	**Input + Output-Based Measures**	**Total**
TECHNOLOGY	Low	584 (53.53)	507 (46.47)	1091
	High	542 (49.63)	550 (50.37)	1092
QUALITY	Low	612 (56.10)	479 (43.90)	1091
	High	514 (47.07)	578 (52.93)	1092
SPEED	Low	637 (58.39)	454 (41.61)	1091
	High	489 (44.78)	603 (55.22)	1092
UNCERTAINTY	Low	430 (47.25)	480 (52.75)	910
	High	696 (54.67)	577 (45.33)	1273
	Total	1126	1057	2183

OUTPUT = 1 when the plant uses output performance measures (i.e. rewards for individual performance, rewards for group performance or gain sharing) and =0 otherwise. TECHNOLOGY is the factor loading of the third factor on initiatives implemented by plants in the sample (see Table 2). Similarly, QUALITY INITIATIVES and SPEED are the corresponding factor loadings of the 1st and 2nd factors in Table 2. UNCERTAINTY is first-pass quality yield of primary products. We classified TECHNOLOGY, QUALITY MANAGEMENT, SPEED and UNCERTAINTY as LOW when their values were below the median and as HIGH otherwise.

Table 3b: Descriptive Statistics --- Choice of Performance Measures, Product/Process Characteristics

				Input + Output-Based Measures (Row % in Parenthesis)			
		Input-Based Measure	**Input + Output-Based Measures**	**Individual Output Measure**	**Individual + Group**	**Group Output Measure**	**Total**
MIX	Low	330 (53.48)	287 (46.52)	82 (28.57)	81 (28.22)	124 (43.20)	617
	High	796 (50.83)	770 (49.17)	249 (32.33)	217 (28.18)	304 (39.49)	1,566
VOLUME	Low	510 (52.85)	455 (47.15)	168 (36.92)	118 (25.93)	169 (37.14)	965
	High	616 (50.57)	602 (49.42)	163 (27.08)	180 (29.90)	259 (43.02)	1,218
FLOW	No	364 (51.41)	344 (48.59)	94 (27.33)	116 (33.72)	134 (38.95)	708
	Yes	762 (51.66)	713 (48.34)	237 (33.23)	182 (25.53)	294 (41.23)	1,475
ORDER	No	303 (52.51)	274 (47.49)	67 (24.45)	85 (31.02))	122 (44.52)	577
	Yes	823 (51.25)	783 (48.75)	264 (33.71)	213 (27.20)	306 (39.08)	1,606
UNION	No	724 (48.59)	766 (51.41)	254 (33.16)	228 (29.77)	284 (37.08)	1,490
	Yes	*402 (58.01)*	*291 (41.99)*	*77 (26.46)*	*70 (24.06)*	*144 (49.48)*	693
TOTAL		1,126	1,057	331	298	428	2183

MIX and Volume reflect the primary product mix of a plant; Plants were asked in the survey regarding whether their product mix is high (low) in Volume or in Mix. FLOW=1 indicates the nature of the operation of the plant is process (not discrete) oriented. ORDER=0 indicates the primary order fulfillment build to stock; . Union=1 reflects the plant is represented with 100% or some of its workers.

Table 4: Logit Regression: Exclusively Input versus Input + Output Based Performance Measure

Variable	Coefficient (Wald $\chi 2$)	Marginal Effects
INTERCEPT	-1.159*** (10.82)	-0.274
TECHNOLOGY	0.603** (4.144)	0.142
QUALITY MANAGEMENT	1.675*** (30.40)	0.396
SPEED	1.740*** (34.37)	0.412
UNCERTAINTY	-0.494*** (9.06)	-0.117
MF PRACTICES	-0.0698 (0.08)	-0.017
ORDER	0.1070 (1.07)	0.025
MIX	0.1036 (1.018)	0.025
VOLUME	-0.0684 (0.49)	-0.016
PROCESS	-0.1222 (1.56)	-0.029
UNION	-0.003*** (9.58)	-0.001
SIZE	0.102** (4.84)	0.024
AGE	-0.156*** (7.754)	-0.037
Likelihood Ratio	120.627	

* . **, *** Significant at the 10%, 5%, 1% level

OUTPUT = 1 when the plant uses output performance measures (i.e. rewards for individual performance, rewards for group performance or gain sharing) and =0 otherwise. TECHNOLOGY is the standardized factor loading of the third manufacturing initiatives factor in Table 2. QUALITY MANAGEMENT is the standardized factor loading of the first manufacturing initiatives factor in Table 2. SPEED is the standardized factor loading of the second manufacturing initiatives factor in Table 2. UNCERTAINTY is the inverse rank of the plant's first-pass quality yield of primary products. MF indicates how much progress the firm has made towards world-class manufacturing status (4-point scale). SPECIAL ORDER is a dummy variable that is equal to 0 when the plant's primary order fulfillment is to build to stock and 1 otherwise. MIX is a dummy variable that is equal to 1 when the plant has a high mix of products and is 0 otherwise. VOLUME is a dummy variable that is equal to 1 when the plant has a high volume of production and is 0 otherwise. PROCESS is a dummy variable that is equal to 1 when the plant has a discrete production process and is 0 otherwise. UNION is the extent to which plant production workers are represented by unions. SIZE is the number of employees that work at the plant's location. AGE is the number of years the plant has operated. Marginal effects are calculated at the mean of the independent variables.

Table 5: Descriptive Statistics – Individual versus Group Performance Measures

		Input + Output-Based Measures: Individual Versus Group Incentives (γ versus γ_G) (Row % in Parenthesis)		
		Individual Output	Group Output	Total
TECHNOLOGY	Low	150 (41.55)	211 (58.45)	361
	High	181 (45.48)	217 (54.52)	398
QUALITY MANAGEMENT	Low	184 (49.60)	187 50.40)	371
	High	147 (37.89)	241 (62.11)	388
SPEED	Low	165 (47.01)	186 (52.99)	351
	High	166 (40.69)	242 (59.31)	408
UNCERTAINTY	Low	137 (40.65)	200 (59.35)	337
	High	194 (45.97)	228 (54.03)	422
		331	428	759

Group (γ_G) = 1 when the plant uses group-based output performance measures (i.e. rewards for group performance or gain sharing) and =0 otherwise (i.e. INDIVIDUAL (γ)=1). TECHNOLOGY is the standardized factor loading of the third manufacturing initiatives factor in Table 2. QUALITY MANAGEMENT is the standardized factor loading of the first manufacturing initiatives factor in Table 2. SPEED is the standardized factor loading of the second manufacturing initiatives factor in Table 2. UNCERTAINTY is first-pass quality yield of primary products. We classified TECHNOLOGY, QUALITY MANAGEMENT, SPEED and UNCERTAINTY as LOW when their values were below the median and as HIGH when they were equal to or above the median. We constrained the sample to plants that use output performance measures on exclusively an individual basis or group basis.

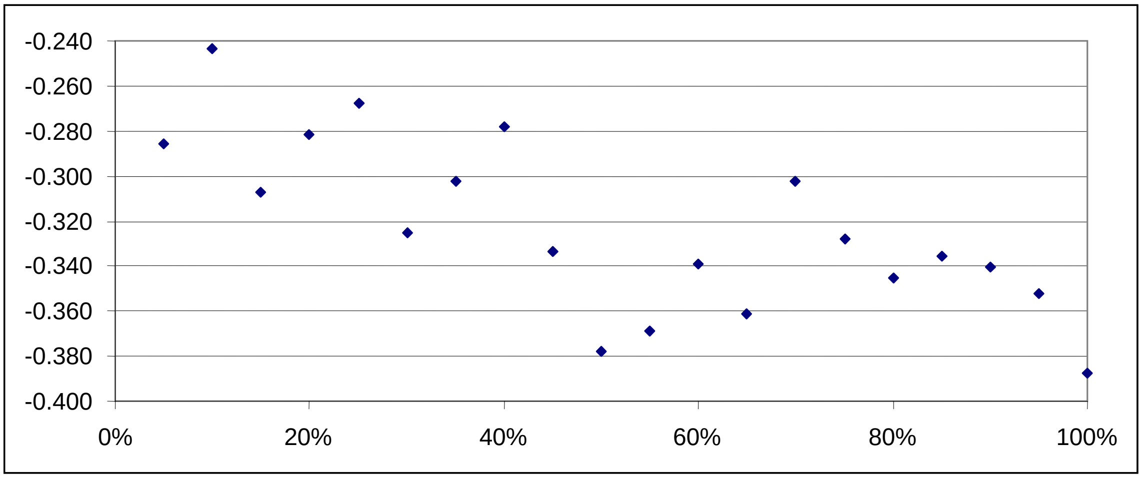
Table 6: Logit Regression: Choice of Individual Versus Group-Based Output Performance Measures

Variable	Coefficient (Wald $\chi2$)	Marginal Effects	Coefficient (Wald $\chi2$)	Marginal Effects
	Without Interactive		With Interactive	
INTERCEPT	-0.280 (0.21)	-0.200	-0.691 (0.54)	-0.170
TECHNOLOGY	-0.979* (3.71)	-0.252	-0.192 (0.02)	-0.047
QUALITY INITIATIVES	1.741*** (10.55)	0.405	2.676 (2.43)	0.659
TECHNOLOGY × QUALITY	--	--	-1.810 (0.33)	-0.446
SPEED	0.594 (1.27)	0.135	0.584 (1.182)	0.141
UNCERTAINTY	-0.117 (0.16)	-0.032	-0.111 (0.15)	-0.027
MF PRACTICES	0.312** (5.02)	0.075	0.313** (5.06)	0.077
ORDER	-0.495*** (6.693)	-0.119	-0.494*** (6.89)	-0.122
MIX	-0.014 (0.005)	-0.009	-0.009 (0.00)	-0.002
VOLUME	0.219 (1.74)	0.060	0.222 (1.79)	0.055
PROCESS	-0.055 (0.10)	-0.015	-0.053 (0.10)	-0.013
UNION	0.008*** (14.57)	0.002	0.008*** (14.64)	0.002
SIZE	0.024 (0.09)	0.009	0.023 (0.09)	0.006
AGE	-0.182 3.745		-0.182* (3.742)	-0.045
Likelihood Ratio	59.892		60.184	

* . **, *** Significant at the 10%, 5%, 1% level

Group (γ_G) = 1 when the plant uses group-based output performance measures (i.e. rewards for group performance or gain sharing) and =0 otherwise (i.e. INDIVIDUAL (γ)=1). TECHNOLOGY is the standardized factor loading of the third manufacturing initiatives factor in Table 2. QUALITY MANAGEMENT is the standardized factor loading of the first manufacturing initiatives factor in Table 2. SPEED is the standardized factor loading of the second manufacturing initiatives factor in Table 2. UNCERTAINTY is first-pass quality yield of primary products. MF indicates how much progress the firm has made towards world-class manufacturing status (4-point scale). SPECIAL ORDER is a dummy variable that is equal to 0 when the plant's primary order fulfillment is to build to stock and 1 otherwise. MIX is a dummy variable that is equal to 1 when the plant has a high mix of products and is 0 otherwise. VOLUME is a dummy variable that is equal to 1 when the plant has a high volume of production and is 0 otherwise. PROCESS is a dummy variable that is equal to 1 when the plant has a discrete production process and is 0 otherwise. UNION is the extent to which plant production workers are represented by unions. SIZE is the number of employees that work at the plant's location. AGE is the number of years the plant has operated. Marginal effects are calculated at the mean of the independent variables. We constrained the sample to plants that use output performance measures on exclusively an individual basis or group basis.

Figure 2: Average Interactive Effect Specific Knowledge and the Value of Knowledge Sharing



The Y-axis represents the mean interactive effect of the interaction of specific knowledge and the value of knowledge sharing for plants in their respective specific knowledge group (5% sample increments), while the X-axis represents the specific knowledge groups (*TECHNOLOGY*). We used the procedure described in Ai and Norton (2003) to calculate the interactive effect. Note, that while there is a consistent pattern, most of the individual interactive effects are not significant at conventional significance levels.