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

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Abstract

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This paper develops and empirically tests a parsimonious model of how specific knowledge and the value of knowledge sharing influence manufacturing plants' incentive design choices. Our results confirm the prediction that increases in the extent of agents' specific knowledge and the value of knowledge sharing are associated with greater (less) reliance on output (input) performance measures. Moreover, consistent with our model's prediction, we find that plants rely more on group-based (as opposed to individual-based) output performance measures when the value of knowledge sharing is higher, or the extent of agents' specific knowledge is lower. Finally, consistent with previous research, we find that as output performance measures become noisier, firms rely less on these measures in incentive contracts.

Keywords: specific knowledge; knowledge sharing; incentive design; group incentives.

Data Availability: Contact IndustryWeek (http://www.industryweek.com) with questions concerning data availability

I. INTRODUCTION AND PRIOR RESEARCH

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 that generally replace fixed hourly pay for production employees with variable compensation. Under the new compensation arrangements, some production workers are paid exclusively based on their individual input (e.g., number of hours worked), while others receive both pay based on input measures and also compensation based on their individual and/or group output. To explain this rich variety of compensation structures, we develop and test a parsimonious model of optimal production incentives.

We find considerable diversity in how the 1,780 U.S. manufacturing plants in our sample compensate their employees. Approximately one-half of all sample plants determine pay using only input performance measures while the remaining plants use a combination of input and output measures (Panel A of Table 1). Further, the latter group is divided approximately evenly between plants using exclusively individual-based output performance measures, plants using a combination of individual-based and group-based output performance measures, and plants using exclusively 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 value created when employees share this knowledge. Here specific knowledge is information that pertains to production employees' decision-making but is very costly to communicate to management (Jensen and Meckling 1992).

To address the role of specific knowledge and how it is shared in manufacturing environments, we extend Raith's one-agent two-task model (2008) by introducing a second agent and allowing each agent to have private information on the productivity of both individual and group tasks. The agents' observable and contractible efforts across two tasks, together with exogenous state uncertainty, determine the principal's total output. The agents can improve their group-task related knowledge by sharing their information, and when the principal uses output performance measures to determine the agents' pay, this gives the agents incentive to utilize their specific knowledge to benefit the principal. Although pay based on output performance measures is typically riskier than pay based on input performance measures, the cost of this additional risk may be offset by the potential gains from exploiting the agents' specific knowledge.

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 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.

Prior research has addressed the tradeoffs involved in rewarding agents based on input versus output performance measures, and the corresponding tradeoffs between using measures of individual versus group output. However, this work typically focuses on one of the two tradeoffs whereas our model incorporates both. Prendergast (2002) demonstrates when optimal contracts will shift from using less risky input measures to using riskier output measures in order to motivate agents to use their specific knowledge. Hence, the value of agents' private information

can increase in more uncertain environments, and consequently delegation and output performance measures will be observed more frequently in higher risk environments.

Other prior research documents that it is common in modern production environments to reward production workers based on both individual outputs and on group outputs. For example, in their study of 249 firms in the automotive and computer industries, Ittner and Larcker (1995) find that although individual performance tends to outweigh team performance in determining compensation, the mean (median) ratio of team performance importance to individual performance importance was 0.797 (0.750). Further, Shaw and Schneier (1995) find that in Fortune 100 companies, rewards for individual performance remain important even when firms rely heavily upon teams.

Existing theory offers diverse explanations for the use of group-based output measures. Agency literature on moral hazard (Holmstrom 1982; Holmstrom and Milgrom 1994) establishes that group-based incentives can create valuable externalities, even when agents have limited decision-making discretion, because group-based output measures can provide additional contracting information beyond that provided by individual-based performance measures. Consistent with this prediction, 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.

In contrast to these studies, we emphasize how specific knowledge and the value of sharing this knowledge play important roles in the choice between individual-based output and group-based output measures. Prior literature demonstrates that when specific knowledge is dispersed across individuals, assigning decision-rights to a team of employees rather than to individual employees can improve the joint allocation of decision rights and specific knowledge (Wruck

and Jensen 1994). For example, Keating and Wruck (1993) report how the implementation of a TQM program at Sterling Chemicals succeeded because quality teams elicited the specialized knowledge of clerks, craftsmen and machine operators to overcome significant operational bottlenecks. Similarly, Sprinkle and Williamson (2004) describe how John Deere Corporation shifted from individual-based incentives to group-based incentives to encourage greater information sharing, cooperation and motivation among employees.

This study makes three contributions to the literature on management control systems and incentive system design. First, whereas previous studies have focused on the informativeness of performance measures (e.g., Murphy 2001; Bushman et al. 1995) and documented settings in which noisier signals will be weighted less heavily in incentive arrangements, we demonstrate that in other settings the optimal incentives based on firm outputs (noisier signal) become sharper when agents have specific knowledge about the state of the firm's production technology. Second, we demonstrate how specific knowledge and knowledge sharing influence firms' choices between individual-based versus group-based incentives, an aspect of incentive design that previously has received less attention, and we do so in a model that simultaneously incorporates the choice between input and output performance measures. Finally, our sample of 1,780 plants spans all the two-digit manufacturing SIC codes, which gives our study greater generalizability than previous research that relies on either relatively small samples (e.g., Bushman et al. 1995) or results from a single industry (e.g., Ichniowski et al. 1997).

Section II develops a two-agent model in which both agents take observable actions and have specific knowledge they can share. Section III develops testable hypotheses based on the model in section II, and describes our empirical tests. The results of our empirical tests are presented in

section IV, and section V reports the results of several robustness tests. Finally, section VI presents a summary and conclusions.

II. THEORETICAL FRAMEWORK

Consider a manufacturing setting in which the principal employs two workers, each of whom allocates her total effort over two tasks – individual and group production. Worker *i* devotes effort $a_i \in R^+$ to producing individual output (Y_i) and effort $a_{iG} \in R^+$ to producing group output (Y_G).

Production: Total output Y is the sum of individual and group output, $Y = \sum_i Y_i + Y_G$ where $i=1, 2$. 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 $min\{(a_{iG} + a_{jG}) \theta_G , 1\}$.

Production technology: The productivities of the plant's individual and group production technologies are $\theta_i = \bar{\theta}(1+ \tau_i)$ and $\theta_G = \bar{\theta}(1+ \tau_G)$, where $\bar{\theta}$ is a scaling parameter and $\tau_i, \tau_G \in \{1, -1\}$ are indicator variables (*High=1, Low= −1*) for true, unobservable productivity. Each worker receives two private signals, $\{s_i, s_{iG}\}$, where s_i , $s_{iG} \in \{1, -1\}$, that are potentially informative about the true productivity of the two tasks. We assume that workers cannot communicate their private productivity signals (specific knowledge) to the principal. The prior probability of high and low productivity is: $p(\tau = 1) = p(\tau = -1) = ½$.

Specific knowledge and knowledge sharing: Following Raith (2008), we define the following information structure for each worker's individual production task: $p(s_i| \tau_i) = p(\tau_i|s_i) =(1+\tau_i s_i k)/2$, where τ_i, $s_i \in \{1, -1\}$. Parameter $k \in [0,1]$ represents the extent of workers' specific knowledge in a given plant. As $k \rightarrow 0$, an agent's specific knowledge becomes less informative, and the

posterior equals the prior of ½. As k increases, the worker's specific knowledge becomes more informative about the plant's production technology. For $k > 0$, when $\tau_i = s_i$ (i.e., both are +1 or both are -1), indicating "correct" beliefs, the worker's posterior increases above ½ and the magnitude of the increase is proportional to the strength of the agent's specific knowledge (k). When $s_i \neq \tau_i$ (i.e., an agent's signal does not match the actual state), the worker's posterior is < ½, again in proportion to the strength of the worker's specific knowledge (k).

For the group task we assume that workers can costlessly pool their private signals (s_{iG}, s_{jG}).[1] The information structure with pooled signals follows the same general structure as that of the individual task: $p(s_{iG}, s_{jG} \mid \tau_G) = \frac{1}{4}\left[(1 + s_{iG}\,\tau_G\,k) + \frac{1}{2}(s_{iG} + s_{jG})\,\tau_G\,\rho\right]$, where $\rho \in [0, 1 - k]$ reflects the value of knowledge sharing.[2] The assumptions above imply a joint probability of $1/4$ for all combinations of the two signals (s_{iG}, s_{jG}) and the following posterior probability:

$p(\tau_G \mid s_{iG}, s_{jG}) = \frac{1}{2}\left[(1 + s_{iG}\,\tau_G\,k) + \frac{1}{2}(s_{iG} + s_{jG})\,\tau_G\,\rho\right]$; where $\tau_G \in \{1, -1\}$ and $s_{iG}, s_{jG} \in \{1, -1\}$ (see Appendix for details). When the workers' signals are consistent (i.e., $s_{iG} = s_{jG}$), workers' posterior beliefs increase above $1/2$ in proportion to the sum of the extent of specific knowledge (k) and the value of knowledge sharing (ρ). For example, when both signals are high (i.e., $s_{iG} = s_{jG} = 1$) we have: $p(\tau_G = 1 \mid s_{iG} = s_{jG} = 1) = (1 + k + \rho)/2$. Hence, as $\rho \rightarrow (1-k)$, pooling the two signals resolves all technological uncertainty and the corresponding posterior probability converges to 1. In contrast, as $\rho \rightarrow 0$, the informativeness of workers' combined signals reduces to that in the individual task where each worker relies on his own signal.[3] Moreover, when the group productivity signals are inconsistent (e.g., $s_{iG} = 1$, $s_{jG} = -1$), sharing of information adds no additional value and the conditional posterior probability converges to that with a single individual private signal $\frac{(1 + s_{iG} k \tau_G)}{2}$ (i.e., $p(\tau_G \mid s_{iG} \neq s_{jG})$).

Consequently, we model ρ and k as distinct, but related, concepts. Specific knowledge (k) captures the informativeness of employees' knowledge concerning the productivity of both individual and group tasks, while ρ is applicable only in group tasks and reflects the extent to which, by sharing their signals, employees can enhance the overall value of their individual knowledge, thereby reducing the uncertainty associated with the group task. In practice, the value of knowledge sharing (ρ) is often high when workers' have more extensive specific knowledge (k). For example, in project teams a diverse group of specialized workers (high k) may be temporarily assigned to a complex project that is too complicated for workers to solve on their own (high ρ). However, in other settings workers' specific knowledge may be high, while the value of knowledge sharing is low, or vice-versa. For example, in a traditional manufacturing setting, workers are often assigned to a particular machine for months or even years at time, which makes them intimately familiar with their narrowly defined tasks (high k). To the extent that workers focus only on their narrowly defined job responsibilities, there is relatively less value to sharing knowledge in this environment. Further, workers' specific knowledge may be relatively low in other settings in which workers are permanent members of self-contained, identifiable work units that conduct repetitive operations. However, in such settings, TQM teams can significantly increase productivity by encouraging workers to pool the information they encounter during their daily routines (high ρ). For example, Keating and Wruck (1993) describe an interview with a manager at Sterling Chemicals who stated that:

> "*The quality process works,…People must be willing to work together, willing to break down barriers. We have to accept the fact that much of the expertise resides in the people who are doing the work. …. Previous management put together a group of chemical engineering PhDs to find a way to get the lactic acid concentrator to work better. They couldn't do it. Solutions identified by one of our quality teams saved us $2.5 million per year. The ideas came from hourly workers who spend every day of the week working with the process, not from engineers.*"

Workers' Utility: Workers are risk-neutral with utility $w–d(a_i,a_{iG})$, where w is compensation and the disutility of action is $d(.) = d(a_i^2+a_{iG}^2)$. We assume that workers have limited liability such that their compensation is always positive, and that the participation constraints are such that we can set fixed salary at zero.[4] In addition, although linear contracts are not necessarily optimal in this setting, for tractability we assume that each worker's compensation is linear in three contractible measures: $w = \beta A_i + \gamma_i y_i + \gamma_G y_G$ where:

1. a_i ,and a_{iG} are individual input performance measures with associated payment of β per unit of input. We assume that the principal has perfect information on each worker's total effort $A_i = a_i + a_{iG}$, but not on specific effort components.
2. y_i is the individual output performance measure with associated payment γ_i;
3. y_G is the group output performance measure with associated payment γ_G.

Worker i's utility function becomes:

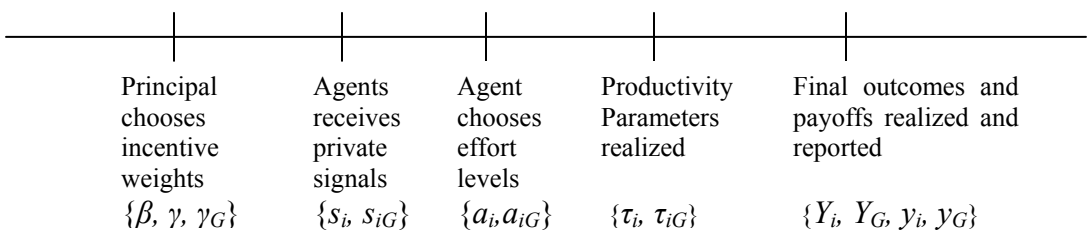
$$U(A_i) = w(A_i) - d(a_i, a_{iG}) = \beta A_i + \gamma_i\ y_i + \gamma_G\ y_G - d(a_i^2 + a_{iG}^2)\,. \tag{1}$$

Performance Measurement: Output performance measures (y) are related to the corresponding actual outputs (Y) 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, $p(y_G = Y_G) = \frac{(2-e)}{2}$. Larger values of the common noise term "e" reflect greater measurement error.[5]

Design Choices: Several design features of our model should be noted. First, to focus on specific knowledge and knowledge sharing, we assume that the principal has perfect information on each worker's total input (i.e., total effort (A_i) is perfectly observable) but not on measures of output. This assumption shifts the emphasis from the traditional moral hazard problem to a delegation problem in which workers have specific knowledge that is essential for productivity.

Second, the principal's ability to observe workers' total effort, but not the distribution of total effort across the individual and group tasks reflects, for example, the routine tracking of employees' total hours worked but not the time devoted to each task.[6] Finally, Raith (2008, 8-9) discusses how his analysis of compensation based on inputs versus outputs can be reinterpreted to compare the use of individual incentives, which are associated with lower uncertainty like inputs, versus group incentives, which are associated with greater uncertainty like outputs. We take a related but different approach by explicitly modeling both specific knowledge and information sharing as distinct characteristics of the firm's environment. This enables us to derive predictions that distinguish the effect of these two characteristics, particularly in our Proposition 3.

Time Line:



Optimal incentive contract: To solve for workers' optimal effort levels, we first provide the following expression for the expected value of individual performance measure y_i conditional on (θ_i, a_i):

$$E\left[\, y_i(\theta_i, a_i)\,\right] = \left(\frac{2-e}{2}\right) \times \left(\theta_i\ a_i\right) + \left(1 - \frac{2-e}{2}\right) \times \left(1 - \theta_i a_i\right) = \frac{e}{2} + (1-e) \times \theta_i\ a_i\,. \tag{2}$$

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

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

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

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

where $\hat{\theta}_i = E\left[\,\theta_i \,|\, s_i\,\right] = \bar{\theta}\left[1 + s_i\, k\,\right]$ and $\hat{\theta}_{iG} = E(\theta_G \,|\, s_{iG}\, s_{jG}) = \bar{\theta}\left[\,1 + s_{iG}\;k + \frac{\left(s_{iG} + s_{jG}\right)}{2}\;\rho\right]$. (5)

The first-order conditions on worker *i's* actions a_i^* and a_{iG}^* (individual and group tasks) become:

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

Denoting the total output as $\boldsymbol{Y} = \sum_i Y_i + Y_G$ and worker's private signals as $\boldsymbol{S} = \{\,s_i, s_j, s_{iG}, s_{jG}\,\}$, the principal's expected payoff conditional on the productivity parameter $\theta = (\theta_i, \theta_j, \theta_G)$ and agents' private signal $\boldsymbol{S}$ is: $E(\pi) = E\big(Y(\theta,S)\big) - \sum_i w_i\,(\theta,S)$

$$= E\left(\sum_i Y_i(\theta_i, S) + Y_G(\theta,S) - \left(\beta\left(A_i + A_j\right) + \gamma\,E\big(y_i(\theta,S) + y_j(\theta,S)\big) + 2\gamma_G\,E\big(y_G(\theta,S)\big)\right)\right). \quad (7)$$

Using the expected productivities (5) in equation (6) and substituting the resulting expression, together with equations (2) and (3) into the principal's ex-ante profit function (7), we next take the expectations over the 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 equation (A2) in the Appendix for the resulting optimal incentive weights, β, y_i, and y_G.

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 incentive weights that the plants place on input and output-based performance measures (all proofs are in the Appendix).

Proposition 1: As the extent of workers' specific knowledge (*k*) increases, the optimal weight on the input performance measure decreases ($\partial\beta/\partial k < 0$), and the

optimal weights on both output performance measures increase ($\partial\gamma/\partial k > 0$ and $\partial\gamma_G/\partial k > 0$).

Proposition 1 parallels Raith's (2008) result that more specific knowledge calls for a greater weight on output performance measures (γ and γ_G). Therefore, even with perfect input performance measures, noisy output performance measures receive increasing weight 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 value of knowledge sharing (ρ) on the optimal incentive weights placed on input and output performance measures. Larger values of ρ reflect environments in which workers who pool their private signals can make relatively more precise inferences concerning group productivity, θ_G.

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 both output performance measures increase ($\partial\gamma/\partial\rho > 0$ and $\partial\gamma_G/\partial\rho > 0$).

Proposition 2 establishes that as the value of knowledge sharing (ρ) increases, the optimal incentive weights will decrease on input measures and increase on output measures. The increase in the incentive weight on group-based output (γ_G) follows directly because an increase in ρ means that the workers are now pooling more diagnostic signals, which increases the expected productivity of effort on the group task. The result that the weight on individual output (γ) should also increase is less direct. The shift in the optimal incentive mix towards more weight on the group-based output performance measures (γ_G) also reduces the input incentive weight (β).

However, because β *i*s the incentive weight on effort on both the individual and group tasks (recall that the principal observes only total effort, not the components), reducing β also indirectly reduces the agent's incentive to work on the individual task. Therefore, the principal must increase the weight on the individual-based output performance measures to compensate for the reduced input incentive weight, β. Hence, an increase in the value of knowledge sharing (ρ) results not only in greater incentive weight on group-based output performance measures (γ_G), but also greater incentive weight on individual-based output performance measures (γ). This leads to the interesting question of the relative influence of the value of knowledge sharing (ρ) and the extent of workers' specific knowledge (k) on individual versus group-based output performance measures (γ , γ_G), which we address next.

Proposition 3: The relative weight placed on group versus individual-based output performance measures is decreasing in workers' specific knowledge (i.e., $\partial(\gamma_G - \gamma)/\partial k < 0$ if $k > ½$) and increasing in the extent of the value of knowledge sharing (i.e., $\partial(\gamma_G - \gamma)/\partial \rho > 0$).

Proposition 3 characterizes the influence of the extent 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 (γ). The intuition behind Proposition 3 comes from the differential impact that increases in specific knowledge (k) and the value of knowledge sharing (ρ) have on the returns to working on the individual and the group tasks. In particular, while more specific knowledge (k) directly increases the returns to both the individual and the group tasks, the magnitude of the gain to an individual employee from working on the group-task is smaller because the gain is shared with all group members. Consequently, increases in the

extent of workers' specific knowledge (k) shift the relative incentive weight from group-based output performance measures (γ_G) towards individual-based output performance measures (γ).

Further, while the increase in the incentive weight on group-based output performance measures (γ_G) due to an increase in the value of knowledge sharing (ρ) is a direct response to the increased productivity of the group task, the corresponding increase in the incentive weight on the individual-based performance measures (γ) represents an indirect, smaller response as described earlier. Hence, increases in the value of knowledge sharing (ρ) shift the relative incentive weight from individual-based output performance measure (γ) towards group-based output performance measure (γ_G).

Finally, Proposition 4 establishes how the quality of the output performance measure (e) affects the relative weight placed on input versus output performance measures.

Proposition 4: As the noise in the output performance measure (e) increases, the weight on the input performance measure increases ($\partial\beta/\partial e > 0$) and the weights on both output performance measures decrease ($\partial\gamma/\partial e < 0$ and $\partial\gamma_G/\partial e < 0$).

The intuition for $\partial\beta/\partial e > 0$ is straightforward and similar to findings from traditional agency models. Noisier output performance measures are more costly and therefore lead to assigning more weight to input performance measures. As the variance (e) of the output performance measure increases, the link between effort and performance weakens, which reduces employees' incentives to exert effort. We next describe our data and empirical tests.

III. EMPIRICAL MODEL

Sample Selection and Data Description

We obtain our data from the *4th Annual IndustryWeek Census of Manufacturers* (2000 Survey). The plants surveyed had two-digit SIC codes of 20-39, and survey respondents held titles such as manufacturing manager and plant manager, and reported on plant-level incentive features and other manufacturing practices at their facility. A total of 3,006 completed surveys were received (response rate 11%). We eliminate independently owned plants with fewer than 100 employees, because Henneman and Berkley (1999) suggest that smaller firms are more likely to rely on informal appraisal procedures.[7] Screening the resulting sample for missing information further reduced our sample to 1,780 observations. This sample reflects an industry distribution comparable to the COMPUSTAT population, and covers all two-digit manufacturing SIC codes with the most plants in Industrial and Commercial Machinery (Panel B of Table 1).[8] Panel C of Table 1 reports descriptive statistics for the sample plants, including sales, number of employees and plant age. The results indicate that the typical plant in our sample employs between 100 and 250 employees and has operated for over 20 years.

[Insert Table 1 here]

Translating Model Implications to Empirical Tests

Our model makes predictions concerning the incentive weights placed on alternative performance measures. Our empirical tests would ideally be based on the corresponding incentive weights in employees' compensation contracts. Unfortunately, the survey asked whether the plant had adopted various categories of input performance measures, as well as individual-based and group-based output performance measures, but did not collect the corresponding incentive weights. As a result, we design our empirical analysis to estimate the

relative likelihood that plants use various categories of performance measures rather than to estimate the specific incentive weights they assign to these performance measures.[9]

To express our model's predictions in terms of the relative likelihood of plants using different categories of performance measures, we assume that whatever plant characteristics make it optimal to assign greater incentive weight to a particular performance category also increase the relative likelihood that the plant will find it cost-beneficial to employ such measures. For example, in environments in which employees have more extensive specific knowledge, Proposition 1 predicts that the firm will increase the incentive weights on output measures. Our assumption then implies that the greater is employees' specific knowledge, the more likely the plant will be to compensate production employees on output performance measures.

Because our analysis addresses the *relative* likelihood that plants will adopt certain categories of performance measures, we must analyze measures that have been adopted by some, but not all plants. We assume that all plants employ a set of fundamental input performance measures, and further that all input performance measures are individual-based rather than group-based. The assumption that all plants base compensation to some extent on individual inputs reflects the fact that plants typically track such input measures as each employee's time spent on the job, skill and technical certifications, etc. However, employee compensation generally will not depend on the work records or skills of other employees; i.e., on group-based input measures. Therefore, we assume that all sample plants use individual-based input measures, but no plants use group-based input measures, and we then focus our empirical analysis on the relative likelihood that sample plants employ individual-based or group-based output performance measures. Given this perspective, we next translate the model's propositions into specific hypotheses.

Proposition 1 predicts that greater specific knowledge results in larger incentive weights on individual-based and group-based output measures. Translating this reasoning from incentive weights to the relative likelihood of incentive forms yields:

H1: The greater is workers' specific knowledge in a manufacturing environment, the more likely plants are to use output performance measures.

Similarly, Proposition 2 predicts that the weight on output performance measures increases as the value of information sharing among plant workers increases. Our second hypothesis translates this result concerning incentive weights to a prediction concerning the relative likelihood that the plant will employ output performance measures:

H2: The greater the value of knowledge sharing in a manufacturing environment, the more likely a plant is to use output performance measures.

Next, Proposition 3 makes predictions concerning the relative influence of the value of knowledge sharing on individual-based output versus group-based output performance measures. Because we do not have data on specific incentive weights, we are unable to discern the relative importance of individual output and group output performance measures in plants that use both types of output measures. Therefore, for this analysis we include only plants that use either exclusively individual-based output measures or exclusively group-based output measures. In turn, we formulate our hypotheses in terms consistent with this reduced sample. First, according to Proposition 3, increases in the level of workers' specific knowledge decrease (increase) the relative likelihood that these plants use exclusively group-based (individual) output performance measures. Second, plants that use output performance measures are more likely to use

exclusively group-based (individual-based) output performance measures when the value of knowledge sharing among workers is relatively high (low).The preceding discussion results in the following hypothesis:

H3: As the extent of specific knowledge increases, the likelihood of using exclusively group-based (individual-based) output performance measures decreases (increases). Conversely, as the value of knowledge sharing increases, the likelihood of using exclusively group-based (individual-based) output performance measures increases (decreases).

Finally, in a similar manner we develop Hypothesis 4:

H4: As the noise in output performance measures increases, the likelihood of using output performance measures decreases.

Construction of Dependent Variable

As discussed above, the nature of our data requires that we estimate the likelihood of plants employing various categories of performance measures. Further, we assume that all plants employ a set of individual-based input performance measures and no plants use group-based input performance measures. Therefore, we focus our empirical tests on whether plants have adopted individual-based output performance measures and/or group-based output performance measures. Survey respondents indicated whether their plant implemented the following forms of compensation for production workers (respondents could select multiple responses): pay for knowledge, pay for skills, profit sharing, gain sharing, rewards for team performance, rewards for individual performance, other, and no incentives. We classify plants as using output measures

(*OUTPUT*=1) if they selected one or more of the following responses: gain sharing, rewards for team performance, rewards for individual performance. We further classify these plants as using group-based output measures (*GROUP*=1) if they indicated their plant used gain sharing or rewards for team performance, and we classify plants as using individual-based output measures if they indicated their plant used rewards for individual performance.

We treat responses of "pay for knowledge" and "pay for skills" as indicating that the plant uses input performance measures. For several reasons, we do not classify plants with a "profit sharing plan" as using an output performance measure. First, profit sharing plans generally create only a weak and deferred association between outcomes and production workers' compensation. In fact, Blinder (1990) and Blasi (1990) document that the majority of company-wide profit sharing plans provide deferred compensation in order to achieve tax and pension planning advantages. Second, Welbourne and Gomez-Mejia (1995) argue that profit sharing plans are less effective than gain sharing plans in creating output-based incentives because production workers find it difficult to understand how their inputs translate into outputs. Finally, because profit sharing contributions are usually proportional to employees' income, they generate strong incentives only for more highly paid middle and upper management.

Explanatory Variables

We next describe our proxies for specific knowledge and knowledge sharing and their relation to prior literature.

Specific Knowledge: Consistent with Jensen and Meckling (1992), we define specific knowledge as knowledge that is valuable to decision-making but very costly to transfer to managers or supervisors. Examples include knowledge of particular idiosyncrasies of customers, machinery, or operational processes.

Direct measures of the extent of specific knowledge in a particular setting are obviously difficult to obtain. To proxy for specific knowledge, we rely on the fact that a large body of empirical evidence concludes that the adoption of new manufacturing production technologies is generally associated with production workers who possess more extensive capabilities, skills and intelligence.[10] For example, using 1988 and 1993 U. S. Bureau of Census Survey of Manufacturing Technology (SMT) data, Doms, Dunne and Troske (1997) examine how plant-level wages, occupational mix, workforce education, and productivity vary with adoption and use of new technologies. They find that plants that use a large number of new manufacturing technologies are more likely to employ more educated and technically skilled workers. Likewise, Capelli (1993) examines changes in skill requirements for production jobs in 93 manufacturing establishments between 1978 and 1986, a period in which major technological developments occurred (e.g., computer-aided design and manufacturing). His findings suggest that in this period, the complexity of production workers' jobs also increased significantly. Similarly, Leigh and Gifford (1999) find that investments in production technology are positively associated with production workers' education level and hours of formal on-the-job training.

Based on the preceding evidence for the association between investments in new technology and employees' technical skills and capabilities, we use a survey item in which respondents categorize their plant as having either no implementation (*NEW TECH*=1), some implementation (*NEW TECH*=2), or extensive implementation (*NEW TECH*=3) of new process equipment/technologies as a proxy for the extent of specific knowledge in each plant.[11]

Value of knowledge sharing: To proxy for the value of knowledge sharing practices within each plant, we use an indicator that captures the percentage of the production workforce participating in empowered or self-directed teams (*EMPOWERMENT*).[12] In a review article on

empowerment in the workplace, Spreitzer (2007, pp. 4-5) identifies information sharing, skill/knowledge-based pay and training as among the "…specific practices that indicate a high involvement or self-managing system…" Similarly, in an analysis of team dynamics, Seibert et al. (2004) use measures of information sharing, boundary setting, and team accountability to define the team climate which they relate to empowerment in organizations. Finally, Ichniowski,et al. (1997) find high correlations among team practices (participation), information sharing (communication) and skills training in their sample of steel mill production processes. These studies provide general support for our use of *EMPOWERMENT* as a proxy for the value of knowledge sharing.[13]

Noise: We use the percentage of output that requires rework (i.e., 100% - first-pass quality yield rate) as a proxy for measurement noise, because we expect this measure to be positively associated with production process uncertainty. This uncertainty reflects the stochastic nature of scheduling, inventory and maintenance processes, resulting in noisy measures of production workers' performance. To reduce the influence of outliers, we use the fractional rank of this measure. Thus, plants with greater values of this proxy represent plants with noisier output performance measures.

In addition to our hypothesized variables, we also include several control variables that are potentially correlated with our hypothesized variables. We control for the influence of non-production tasks on production workers by including a dummy variable that is equal to 1 when production workers interact with customers, zero otherwise (*CUST INT*). Because a plant's process technology likely affects both the types of skills required from manufacturing workers and the types of rewards used in the plant, we include several measures to control for production process characteristics. We control for a plant's capital intensity by including a logarithmic

transformation of the dollar value of shipments per plant employee (*CAPITAL INTENSITY*). Further, following the classification by Hayes and Wheelwright (1984, 176-179), we include dummy variables that capture whether a plant's production process has a high mix of products (*MIX*=1, 0 otherwise), produces a large volume of products (*VOLUME*=1, 0 otherwise), is continuous (*CONTINUOUS*=1, 0 otherwise) or is discrete (*DISCRETE*=1, 0 otherwise).

In addition, we control for the extent to which plant production workers are represented by a union (*UNION*), because prior research suggests that unions prefer uniform pay to pay based on individual performance.[14] In particular, Verma (2005) finds that unionized workplaces are less likely to use individual incentive plans compared to nonunion workplaces, but are equally likely to adopt group incentive plans. Therefore, we expect unionization to be negatively associated with the use of individual-based output performance measures, but positively associated with the use of group-based output performance measures.

Further, because Henneman and Berkley (1999) suggest that a firm's size is associated with the use of formal appraisal systems, and Shah and Ward (2003) find that larger plants more often use innovative work practices, we control for plant size using a measure of the number of employees in each plant (*SIZE*).[15]

Prior research also suggests that organizations develop operational routines that change infrequently. In particular, Pil and MacDuffie (1996) suggest that the longer an organization has experience with these practices, the more difficult it is to replace older, inferior practices. Therefore, we include an indicator that captures the number of years that the plant has operated (*AGE*).[16] Finally, we include 2-digit SIC indicator variables to control for industry effects.[17]

IV. EMPIRICAL RESULTS

Univariate Tests

Table 2 presents the results of univariate hypothesis tests using dichotomous measures of our main independent variables (subsequent tests use the full detail available for each variable). We classify plants that implemented new process equipment/technologies as requiring a high degree of specific knowledge (*NEW TECH*=High, Low otherwise), plants that use empowered or self-directed teams as having a high value of knowledge sharing (*EMPOWERMENT*=High, Low otherwise), and plants with an above the median rate of rework as having a high degree of measurement noise (*NOISE*=High, Low otherwise).

To test Hypotheses 1, 2 and 4 we examine the influence of our hypothesized variables on the proportion of plants that use output performance measures. The results of this analysis are presented in column (1) of Table 2. Consistent with our hypotheses we find that the proportion of plants that use output-based performance measures is positively associated with our proxies for specific knowledge (*NEW TECH*) and the value of knowledge sharing (*EMPOWERMENT*), and negatively associated with our proxy for measurement noise (*NOISE*) at $p < 1\%$ (one-tailed). Therefore, our univariate tests provide strong support for Hypotheses 1, 2 and 4.

As explained earlier, to test Hypothesis 3 we restrict our sample to plants that use either exclusively individual-based or exclusively group-based output performance measures, and examine whether our proxies for specific knowledge (*NEW TECH*) and the value of knowledge sharing (*EMPOWERMENT*) are associated with the proportion of plants that use exclusively group-based (as opposed to exclusively individual-based) output performance measures. Consistent with Hypothesis 3, column (2) of Table 2 shows that *EMPOWERMENT* is positively associated with the use of group-based performance measures. However, we find no significant

association between *NEW TECH* and the use of group-based output performance measures. Therefore, our univariate tests provide mixed results for Hypothesis 3.

[Insert Table 2 here]

Multivariate Tests

Columns (1) and (2) of Table 3 present the results of a multivariate logit regression that tests Hypotheses 1, 2 and 4. Consistent with our hypotheses, the coefficients on *NEW TECH* and *EMPOWERMENT* in column (1) are positive and significant at $p < 1\%$ (one-tailed), and the coefficient on *NOISE* is negative and significant at $p < 5\%$. Moreover, in column (2) the magnitude of the marginal effects for our hypothesized variables suggests that they are of significant economic importance. In particular, the results in column (2) show that for a one unit increase in *NEW TECH* and *EMPOWERMENT* (e.g., increase from *NEW TECH*=1 to *NEW TECH*=2), the probability that a plant uses output measures increases by 7% and 6%, respectively.[18] In addition, plants in which production workers interact with customers (*CUST INT*), larger plants (*SIZE)* and younger plants (*AGE*) are more likely to use output performance measures. The remaining control variables are not significantly associated with the use of output performance measures.

In summary, the results reported in columns (1) and (2) of Table 3 are consistent with manufacturing plants using output performance measures to induce production workers to use and share their specific knowledge (*NEW TECH* and *EMPOWERMENT*), particularly when it is less costly to do so because measurement noise is low (*NOISE*).

Columns (3) and (4) of Table 3 present the results of testing Hypothesis 3. Consistent with Hypothesis 3, the coefficient on *NEW TECH* in column (3) is negative and significant at $p < 1\%$, and the coefficient on *EMPOWERMENT* is positive and significant at $p < 1\%$. Moreover, the

results in column (4) show that our hypothesized variables are of significant economic importance. In particular, a one unit increase in *EMPOWERMENT* (*NEW TECH*) increases (decreases) the probability that a plant uses group-based output measures by 9%. In addition, more capital intensive plants (*CAPITAL INTENSITY*), plants that produce a high volume of products (*VOLUME*), plants with a higher proportion of workers represented by unions (*UNION*) and younger plants (*AGE*) are more likely to use group-based output performance measures.

In summary, the results reported in columns (3) and (4) of Table 3 are consistent with group-based (as opposed to individual-based) output performance measures becoming more important when the value of knowledge sharing (*EMPOWERMENT*) is greater and when production workers possess less specific knowledge (*NEW TECH*).

[Insert Table 3 here]

V. ROBUSTNESS TESTS

Including Profit-Sharing as a Group-Based Output Measure

First, to check the sensitivity of our results to excluding profit-sharing plans as a group-based output measure, we repeat our multivariate analysis after recoding plants offering profit-sharing plans as using group-based output performance measures. The results reported in column (1) of Table 4 confirm the earlier findings with respect to Hypotheses 1 and 2, but not Hypothesis 4. In particular, in column (1) the coefficients on *NEW TECH* and *EMPOWERMENT* remain positive and significant at $p < 1\%$. However, although the estimated coefficient on measurement noise (*NOISE*) remains negative, it is not statistically significant. Therefore, our results with respect to how specific knowledge and the value of knowledge sharing influence performance measure choice are robust to the inclusion of profit sharing plans as a group-based output performance measure, but our results for measurement noise are not.

Alternative Contrast for Testing Hypothesis 3

The earlier test of Hypothesis 3 considered only plants that use either exclusively individual-based or exclusively group-based output performance measures, thereby excluding 261 plants that use both types of output measures. For this second robustness check, we include these 261 plants by contrasting plants using either exclusively group-based or group and individual-based output measures with plants using exclusively individual-based output measures. The results in column (3) of Table 4 show that consistent with the earlier findings, the coefficient on *NEW TECH* remains negative and significant at $p < 5\%$, and the coefficient on *EMPOWERMENT* remains positive and significant at $p < 1\%$. Therefore, the results with respect to Hypothesis 3 are robust to including plants that use both individual and group-based output performance measures.

Using *LABOR TRAINING* as an Alternative Proxy for Specific Knowledge

The survey collected data on the average annual hours of formal training received by each plant employee. [19] Because such training is likely to increase production workers' specific knowledge, a measure of the extent of relevant training could potentially be an alternative proxy for specific knowledge. However, Bureau of Labor Statistics (1996) data suggests that much of manufacturing workers' formal training involves issues largely unrelated to specific knowledge (e.g., occupational safety training, communications and quality training). Because we do not have data on the specific nature of the training received by production workers, we use the number of training hours multiplied by the percentage of goods sold attributable to labor costs (*LABOR TRAINING*) as an alternative proxy for specific knowledge. To the extent that the percentage of costs of goods sold attributable to labor costs reflects production workers' skills,

education and other characteristics related to specific knowledge, we expect total training hours weighted by this percentage to be a reasonable proxy for specific knowledge.[20]

Columns (4) and (5) of Table 4 show the results of using *LABOR TRAINING* as a proxy for specific knowledge. Consistent with our earlier findings, the coefficient on *LABOR TRAINING* is positive and significant at $p < 5\%$ when we test Hypothesis 2 (column 4), and negative and significant at $p < 5\%$ when we test Hypothesis 3 (column 5). Our results for the value of knowledge sharing and measurement noise remain unchanged. Therefore, our results are robust to using training for skilled labor as an alternative proxy for specific knowledge.

[Insert Table 4 Here]

VI. DISCUSSION AND CONCLUSIONS

We develop and test a parsimonious model relating specific knowledge, the value of knowledge sharing and measurement noise to manufacturing plants' performance measure choices. Our empirical results provide general support for the prediction that manufacturing plants are more likely to use output performance measures when production workers have greater specific knowledge (proxied by the implementation of new production equipment/technologies) or when it is more valuable to induce production workers to share their specific knowledge (proxied by the percentage of the production workforce participating in empowered or self-directed teams). In addition, consistent with traditional agency models, we find empirical support for our model's prediction that the use of output performance measures is negatively associated with measurement noise (proxied by the percentage of output that requires rework). Moreover, consistent with our model's prediction, we find that when plants use output performance measures, they are more likely to use exclusively group-based (as opposed to

exclusively individual-based) output measures when the value of knowledge sharing is greater and when, production workers possess less specific knowledge.

Our study makes several contributions to the incentive design literature. First, previous empirical studies have predominantly focused on the informativeness of performance measures (e.g., Murphy 2001; Bushman et al. 1995). Our study complements such previous empirical work by showing that, under certain conditions, even when input performance measures are less noisy than output performance measures, principals reward agents based on their output when agents possess sufficient specific knowledge. Second, we demonstrate how specific knowledge and the value of knowledge sharing influence firms' choices between individual-based and group-based incentives, an aspect of incentive design that previously has received less attention, and we do so in a model that simultaneously incorporates the choice between input and output performance measures. Finally, our sample of 1,780 plants spans all the two-digit manufacturing SIC codes, giving our results greater generality than previous research that relies on either relatively small samples (e.g., Bushman et al. 1995) or results from a single industry (e.g., Ichniowski et al. 1997).

Although we performed several robustness tests to corroborate our findings, the use of archival data collected by a third party makes our results subject to several important limitations. First, the survey questions were not designed for our specific hypotheses, and therefore our proxies can only imperfectly capture the underlying constructs, particularly the extent of specific knowledge and the value of knowledge sharing. Second, data on the implementation of manufacturing practices is self-reported, which could potentially bias our findings.

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APPENDIX

Group Task Information Structure

Consider the following general form of the information structure, where the prior probability of high versus low productivity equals: $p(\tau_G = 1) = p(\tau_G = -1) = 1/2$

(s_{iG}, s_{jG})	$P(s_{iG}, s_{jG} \mid \tau_G = 1)$	$p(s_{iG}, s_{jG} \mid \tau_G = -1)$
$(1, 1)$	$\frac{(1+k+\rho)}{4}$	$\frac{(1-k-\rho)}{4}$
$(1, -1)$	$(1+k)/4$	$(1-k)/4$
$(-1, 1)$	$(1-k)/4$	$(1+k)/4$
$(-1, -1)$	$\frac{(1-k-\rho)}{4}$	$\frac{(1+k+\rho)}{4}$

The parameter ρ captures the value of knowledge sharing between workers and $\rho \in [0, 1-k]$. The information structure can be expressed as: $p(s_{iG}, s_{jG} \mid \tau_G) = \frac{1}{4}\left[(1 + s_{iG}\,\tau_G\,k) + \frac{1}{2}(s_{iG} + s_{jG})\,\tau_G\,\rho\right]$.

Based on the information structure of $p(s_{iG}, s_{jG} \mid \tau_G)$ defined above, conditional probability of $p(\tau_G \mid s_{iG}, s_{jG})$ can be expressed as :

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

	$s_{iG} = s_{jG} = 1$	$s_{iG} = -1,\ s_{jG} = 1$	$s_{iG} = 1,\ s_{jG} = -1$	$s_{iG} = s_{jG} = -1$
$p(\tau_G = 1 \mid s_{iG}, s_{jG})$	$(1+k+\rho)/2$	$(1+k)/2$	$(1-k)/2$	$(1-k-\rho)/2$
$p(\tau_G = -1 \mid s_{iG}, s_{jG})$	$(1-k-\rho)/2$	$(1-k)/2$	$(1+k)/2$	$(1+k+\rho)/2$

.

Thus, when workers share their knowledge and receive conflicting signals (e.g., $s_{iG} = -1$, $s_{jG} = 1$) the corresponding posterior probability on the productivity parameter τ_G converges to the prior. As the value of information sharing ρ approaches its maximum value of (1-k), workers can achieve perfect information on productivity by pooling their knowledge; i.e., when $\rho \rightarrow (1-k)$ we have $p(\tau_G = 1 \mid s_{iG}=1, s_{jG}=1) \rightarrow 1$ and $p(\tau_G = -1 \mid s_{iG}=1, s_{jG}=1) \rightarrow 0$.

Expected value of productivity parameter condition on pooled signals (Equation 5)

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}), where s_{iG} , s_{jG} , $\tau_G \in \{1,-1\}$. The information structure defined above implies the following expected group productivity parameter:

$$\begin{aligned}\hat{\theta}_{iG} &= E(\theta_G \mid s_i, s_j) = \sum_{\tau_G} \bar{\theta}\left(1+\tau_G\right) p\left(\tau_G \mid s_{iG}, s_{jG}\right) \\ &= \sum_{\tau_G} \bar{\theta}\left(1+\tau_G\right) \frac{1}{2}\left[(1+s_{iG}\,\tau_G\,k) + \tfrac{1}{2}(s_{iG}+s_{jG})\,\tau_G\,\rho\right]; \text{ where } \tau_G = +1 \; or \; -1. \\ &= \bar{\theta}\left[\,1 + s_{iG}\,k + \frac{(s_{iG}+s_{jG})}{2}\,\rho\,\right].\end{aligned}$$

Derivation of Principal's Expected Profit Function

Substituting into the ex-ante expected profit function equation (7) in the main text for the expected performance measure from equations (2) and (3), the principal's expected profit function can be expressed as:

$$\begin{aligned}E(\pi) \quad &= E_I\left(\left(1-\gamma(1-e)\right)\times\left\lfloor \theta_i\, a_i + \theta_j\, a_j \right\rfloor\right) + E_I\left\lfloor\left(1-2\gamma_G(1-e)\right)\times\left(\theta_G\,(a_{iG}+a_{jG})\right)\right\rfloor \\ &\quad - E_I\left[\,\beta\left(A_i + A_j\right)\right] - e(\gamma+\gamma_G); \qquad \text{(A1)}\end{aligned}$$

where $I = \{s_i, s_j, s_{iG}, s_{jG}, \tau_i, \tau_i, \tau_G\}$

Next, substitute the expected productivities (5) back into (6) for the optimal actions and using the resulting expressions into (A1) and evaluate the expected value of (A1) over the signals (s_i, s_j, s_{iG}, s_{jG}, τ_i, τ_j, τ_G). The expected value of the resulting expression reflects128 permutations (the four signals s_i,s_j,s_{iG} and s_{jG} each have two possible values, as do the three production technology parameters, τ_i,τ_j and τ_G) with corresponding probability:

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

The above leads to the following expression for the principal's ex-ante expected profit:

$$E\pi = \begin{pmatrix} \left(\frac{(1-e)}{d}\right)\left[\gamma(1+k^2)(1-(1-e)\gamma)\right]\bar{\theta}^2 + \left(\frac{(1-e)}{2d}\right)\gamma_G(1-2(1-e)\gamma_G) \\ \left(2+(1-e)\gamma_G\left(2+(\rho+k)^2\right)\right)\bar{\theta}^2 - \beta\left(\frac{2\beta+\left[(1-e)(2\gamma+3\gamma_G)-2\right]\bar{\theta}}{d}\right) - e(\gamma+\gamma_G) \end{pmatrix}.$$

By taking the first order derivative of $E\pi$ with respect to the incentive weights: (β, γ and γ_G) we arrive at the optimal incentive weights:

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

$$\gamma = \frac{(1-e)\,\bar{\theta}^2\left[\left(7k^2+(\rho+k)^2(3+8k^2)\right)-3\right] - de\left(13+8(\rho+k)^2\right)}{2(1-e)^2\left[\left(7k^2+4(\rho+k)^2(1+2k^2)\right)-1\right]\bar{\theta}^2} \tag{A2}$$

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

A necessary condition to ensure interior solution for positive incentive weight requires:

$$(1-e)\,\bar{\theta}^2\left[\left(k^2+(\rho+k)^2(1+2k^2)\right)-1\right] > de(5+4(\rho+k)^2). \tag{A3}$$

Assumption (A3) ensures the numerator of γ_G is positive. It also implies $\left(k^2+(\rho+k)^2(1+2k^2)\right)-1 > 0$; which in turn implies $\left[\left(7k^2+4(\rho+k)^2(1+2k^2)\right)-1\right] > 0$, hence $\beta > 0$. Similarly, one can show (A3) implies $\gamma > 0$.

Proof of Proposition 1: To examine the effects of specific knowledge k on agents' incentive weights, we take the partial from the expressions in (A2) for the optimal incentive weights, we have: $\frac{\partial\beta}{\partial k} = < 0$; similar calculations yield $\frac{\partial\gamma}{\partial k} > 0$ and $\frac{\partial\gamma_G}{\partial k} > 0$.

Proof of Proposition 2: From the expressions in (A2) for the optimal incentive weights, by taking the partial derivative of the incentive weights with respect to the parameter for the value of knowledge sharing ρ; assumption (A3) ensures we have: $\frac{\partial\beta}{\partial\rho} < 0$, $\frac{\partial\gamma}{\partial\rho} > 0$ and $\frac{\partial\gamma_G}{\partial\rho} > 0$.

Proof of Proposition 3: Given that $k \in [0,1]$, we have $k^2 \leq 1$. Using the expressions for optimal incentive weights in (A2), it follows that for $k > ½$, we have $\frac{\partial(\gamma_G - \gamma)}{\partial \rho} = \ > 0$. A similar approach yields: $\frac{\partial(\gamma_G - \gamma)}{\partial k} =< 0$.

Proof of Proposition 4: From the optimal incentive weight expressions in (A2), and assumption (A3) we get $\frac{\partial \beta}{\partial e} = \ > \ 0$. Similar analysis yields:

$$\frac{\partial \gamma}{\partial e} = \frac{\bar{\theta}^2(1-e)\left[\left(7k^2 + (\rho+k)^2(3+8k^2)\right) - 3\right] - d(1+e)\left(8(\rho+k)^2 + 13\right)}{(1-e)^3\left[\left(7k^2 + 4(\rho+k)^2(1+2k^2)\right) - 1\right]\ \bar{\theta}^2}. \tag{A4}$$

The denominator of (A4) is positive because of (A3). Hence, the sign of $\partial\gamma/\partial e$ is determined by the sign of the numerator. Note $(\rho+k) \leq 1$ and $k \leq 1$. Hence the numerator of (A4) can be expressed as:

$\bar{\theta}^2(1-e)\left[\left(7k^2 + (\rho+k)^2(3+8k^2)\right) - 3\right] - d\,e\left(8(\rho+k)^2 + 13\right) - d\left(8(\rho+k)^2 + 13\right)$. It can be shown that for $d \geq \bar{\theta}^2$ we have $d\left(8(\rho+k)^2 + 13\right) \ \geq \ \bar{\theta}^2(1-e)\left[\left(7k^2 + (\rho+k)^2(3+8k^2)\right) - 3\right]$.

Thus, $\frac{\partial \gamma}{\partial e} \ \leq \ 0$; similarly, one can show that $\frac{\partial \gamma_G}{\partial e} \ \leq \ 0$.

TABLE 1
Descriptive Statistics

Panel A. Distribution of Input-Output and Individual-Group Performance Measures

Incentive base	Exclusively input	Column Percentage	Input and output	Column Percentage
Exclusively individual	896	100.0%	249	28.2%
Individual and group	0	0.0%	261	29.5%
Exclusively group	0	0.0%	374	42.3%
Total Number	896		884	1,780
Row Percentage	50.3%		49.7%	100.0%

Panel B. Distribution of sample across industries

2-digit SIC code	Industry	Count	Column Percentage
20	Food and kindred products	71	4.0%
21	Tobacco products	1	0.1%
22	Textile mill products	46	2.6%
23	Apparel and other finished products	13	0.7%
24	Lumber and wood products, except furniture	41	2.3%
25	Furniture and fixtures	34	1.9%
26	Paper and allied products	72	4.0%
27	Printing, publishing, and allied industries	40	2.3%
28	Chemicals and allied products	93	5.2%
29	Petroleum refining and related industries	9	0.5%
30	Rubber and miscellaneous plastics products	132	7.4%
31	Leather and leather products	6	0.3%
32	Stone, clay, glass, and concrete products	41	2.3%
33	Primary metal industries	106	6.0%
34	Fabricated metal products, except machinery	250	14.0%
35	Industrial and commercial machinery	307	17.3%
36	Electronic and other electrical equipment	250	14.0%
37	Transportation equipment	108	6.1%
38	Measuring, analyzing, and controlling instrument	107	6.0%
39	Miscellaneous manufacturing industries	53	3.0%
* Sample covers all 2-digit SIC Manufacturing Industries	Total	1,780	100.0%

Panel C. Sample plant descriptive statistics

Plant characteristic					
Plant age	*< 5 years*	*5-10 years*	*11-20 years*	*>20 years*	
	4.2%	8.3%	19.0%	68.5%	
Plant full-time employees	*< 100*	*100-249*	*250-499*	*500-999*	*> 1000*
	9.5%	53.5%	23.0%	9.2%	4.8%
Sales of parent Corporation ($Million)	*No corporate Parent*	*< $100*	*$100 –499*	*$500-999*	*> $1,000*
	18.9%	17.0%	20.3%	9.4%	34.4%

TABLE 2
Univariate Hypothesis Tests

		(1) Hypotheses 1,2 & 4		(2) Hypothesis 3	
Measure	**High/Low**	**OUTPUT=0**	**OUTPUT=1**	**GROUP=0**	**GROUP=1**
NEW TECH (Specific Knowledge)	Low	155 (64.6%)	85 (35.4%)	26 (41.3%)	37 (58.7%)
	High	741 (48.1%)	799 (51.9%)	223 (39.8%)	337 (60.2%)
	Test Statistic	χ^2=22.52	*p*-value = 0.00	χ^2=0.05	*p*-value = 0.82
EMPOWERMENT (Knowledge Sharing)	Low	321 (65.4%)	170 (34.6%)	72 (50.4%)	71 (49.6%)
	High	575 (44.6%)	714 (55.4%)	177 (36.9%)	303 (63.1%)
	Test Statistic	χ^2=61.35	*p*-value = 0.00	χ^2=8.34	*p*-value = 0.00
NOISE	Low	361 (45.9%)	425 (54.1%)	113 (39.0%)	177 (61.0%)
	High	535 (53.8%)	459 (46.2%)	136 (40.8%)	197 (59.2%)
	Test Statistic	χ^2=10.94	*p*-value = 0.00	χ^2=0.23	*p*-value = 0.63
	N	896	884	249	374

Hypotheses 1, 2 & 4 are tested by contrasting plants that use output performance measures (OUTPUT=1), with plants that do not use output performance measures (OUTPUT=0). OUTPUT is equal to 1 if a plant offers monetary awards for gain sharing, group performance or individual performance, 0 otherwise. Because we do not have data on incentive weights, we test Hypothesis 3 by contrasting plants that use exclusively group-based output measures (GROUP=1), with plants that use exclusively individual-based output measures (GROUP=0). GROUP is equal to 1 if a plant offers monetary awards for gain sharing or group performance, and is equal to 0 if a plant offers monetary awards for individual performance.

For the purpose of this test we dichotomize our independent measures as follows: NEW TECH is Low if a plant has not implemented new process equipment / technologies, and is High if a plant has some or extensive implementation of new process equipment / technologies; EMPOWERMENT is Low if respondents indicate that 0% of the production workforce participates in empowered or self-directed teams, and is High if they indicated that 1-25%, 26-50%, 51-75%, 76-99%, or 100% of the production workforce participates in empowered or self-directed teams; NOISE is Low if the percentage of a plant's output that requires rework is below the median, and is High otherwise.

TABLE 3
Multivariate Logit Regressions

	OUTPUT=1		GROUP=1	
Measure	**(1) Coefficient (*z*-statistic)**	**(2) Avg. Marginal effect (*z*-statistic)**	**(3) Coefficient (*z*-statistic)**	**(4) Avg. Marginal Effect (*z*-statistic)**
NEW TECH	0.32***	0.07***	-0.42***	-0.09***
	(3.75)	(3.86)	(-2.58)	(-2.68)
EMPOWERMENT	0.26***	0.06***	0.44***	0.09***
	(6.53)	(6.91)	(5.85)	(6.65)
NOISE	-0.41**	-0.09**	-0.26	-0.05
	(-2.19)	(-2.20)	(-0.75)	(-0.75)
CUST INT	0.27***	0.06***	0.15	0.03
	(3.14)	(3.20)	(0.94)	(0.94)
CAPITAL INTENSITY	-0.04	-0.01	0.16*	0.03*
	(-0.65)	(-0.65)	(1.61)	(1.63)
MIX	0.06	0.01	0.20	0.04
	(0.53)	(0.53)	(0.87)	(0.88)
VOLUME	-0.14	-0.03	0.37**	0.08**
	(-1.22)	(-1.22)	(1.80)	(1.86)
DISCRETE	-0.06	-0.01	0.18	0.04
	(-0.38)	(-0.38)	(0.60)	(0.61)
CONTINUOUS	-0.06	-0.01	0.00	0.00
	(-0.28)	(-0.28)	(0.01)	(0.01)
UNION	-0.07	-0.02	0.49***	0.10***
	(-1.03)	(-1.03)	(3.72)	(3.98)
SIZE	0.09*	0.02*	0.12	0.02
	(1.54)	(1.54)	(1.15)	(1.16)
AGE	-0.10*	-0.02*	-0.19**	-0.04**
	(-1.57)	(-1.57)	(-1.68)	(-1.70)
Number of obs.	1,779		619	
Likelihood Ratio	159.79		93.87	

Hypotheses 1, 2 & 4 (column 1) are tested by contrasting plants that use output performance measures (OUTPUT=1), with plants that do not use output performance measures (OUTPUT=0). OUTPUT=1 if a plant offers monetary awards for gain sharing, group performance or individual performance, 0 otherwise. We test Hypothesis 3 (column 3) by contrasting plants that use exclusively group-based output measures (GROUP=1), with plants that use exclusively individual-based output measures (GROUP=0). GROUP=1 if a plant offers monetary awards for gain sharing or group performance, and is equal to 0 if a plant offers monetary awards for individual performance.

NEW TECH is respectively equal to 1, 2, or 3 when plants have (1) no implementation, (2) some implementation, or (3) extensive implementation of New Process Equipment/Technologies; EMPOWERMENT is respectively equal to 1, 2, 3, 4, 5, or 6 when respondents report that (1) 0%, (2) 1-25%, (3) 26-50%, (4) 51-75%, (5) 76-99%, or (6) 100% of the production workforce participates in empowered or self-directed teams; NOISE is the fractional rank of the percentage of output that requires rework; CUST INT is equal to 1 if a plant's production employees interact with customers, 0 otherwise; CAPITAL INTENSITY is a logarithmic transformation of the dollar value of plant shipments per employee; MIX is equal to 1 if a plant produces a high mix of products, 0 otherwise; VOLUME is equal to 1 if a plant produces a high volume of products, 0 otherwise; DISCRETE is equal to 1 if a plant has a discrete production process, 0 otherwise; CONTINUOUS is equal to 1 if a plant has a continuous process, 0 otherwise; UNION is respectively equal to 1, 2, or 3 when (1) No workers, (2) Some workers, or (3) All plant production workers are represented by a union; SIZE is respectively equal to 1, 2, 3, 4, or 5 when the plant has (1) less than 100, (2) 100-249, (3) 250-499, (4) 500-999, (5) 1,000 or more employees. AGE is respectively equal to 1, 2, 3 or 4 when it has been (1) less than 5; (2) 5-10; (3) 11-20; or (4) More than 20 years since plant start-up. Coefficients on two-digit SIC code indicators are not reported.

*, **, *** indicate one-tailed statistical significance at the 10%, 5%, and 1% level respectively. Reported marginal effects are computed using the average of discrete or partial changes over all observations (Bartus 2005).

TABLE 4
Robustness Tests

	Alternative Dependent Measure			Alternative Independent Measure	
	(1) Hypotheses 1,2 & 4	(2) Hypothesis 3	(3) Hypothesis 3	(4) Hypotheses 1, 2 & 4	(5) Hypothesis 3
Measure	**OUTPUT2=1**	**GROUP2=1**	**GROUP3=1**	**OUTPUT=1**	**GROUP=1**
NEW TECH	0.30***	-0.39**	-0.30**		
	(3.23)	(-2.30)	(-2.10)		
LABOR TRAINING				0.20**	-0.53**
				(1.67)	(-2.20)
EMPOWERMENT	0.22***	0.37***	0.45***	0.29***	0.44***
	(4.87)	(4.07)	(6.38)	(7.00)	(5.63)
NOISE	-0.15	0.06	-0.19	-0.54***	0.01
	(-0.73)	(0.17)	(-0.63)	(-2.82)	(0.02)
CUST INT	0.36***	0.09	0.32***	0.25***	0.07
	(3.69)	(0.56)	(2.35)	(2.89)	(0.42)
CAPITAL INTENSITY	-0.04	0.10	0.22***	-0.03	0.14*
	(-0.57)	(0.94)	(2.40)	(-0.48)	(1.35)
MIX	0.08	-0.04	0.17	0.11	0.14
	(0.59)	(-0.14)	(0.84)	(0.90)	(0.59)
VOLUME	-0.26**	0.12	0.33**	-0.07	0.43**
	(-2.07)	(0.56)	(1.77)	(-0.62)	(2.02)
DISCRETE	-0.05	0.17	0.07	-0.07	0.04
	(-0.30)	(0.53)	(0.26)	(-0.41)	(0.12)
CONTINUOUS	-0.25	-0.03	0.01	-0.03	0.00
	(-1.19)	(-0.07)	(0.04)	(-0.14)	(0.00)
UNION	-0.40***	-0.06	0.38***	-0.05	0.48***
	(-5.95)	(-0.47)	(3.22)	(-0.73)	(3.52)
SIZE	0.06	0.11	0.18**	0.12**	0.05
	(0.94)	(0.97)	(1.90)	(2.09)	(0.51)
AGE	-0.05	-0.04	-0.14*	-0.11**	-0.17*
	(-0.69)	(-0.29)	(-1.39)	(-1.77)	(-1.46)
Number of obs.	1,779	834	879	1,670	574
Likelihood Ratio	162.98	45.62	106.97	143.08	88.23

Columns (1), (2) and (3) present the results of robustness tests in which we alter our dependent measure. In columns (1) and (2) we include profit sharing plans as group-based output performance measures. OUTPUT2 is equal to 1 if a plant offers monetary awards for profit-sharing, gain sharing, group performance or individual performance, 0 otherwise. GROUP2 is equal to 1 if a plant offers monetary awards for profit-sharing, gain sharing or group performance, and is equal to 0 if a plant offers monetary awards for individual performance. In column (3) we contrast plants using exclusively group-based or using both group-based and individual-based output measures (GROUP3=1), with plants using exclusively individual-based output measures (GROUP3=0). GROUP3 is equal to 1 if a plant offers monetary awards for gain sharing or group performance, and is equal to 0 if a plant offers monetary awards for individual performance, but not for gain sharing or group performance.

Columns (4) and (5) present the results of robustness tests in which we use *LABOR TRAINING* as an alternative proxy for production workers' specific knowledge. *LABOR TRAINING* is the average annual hours of formal training received by each plant employee multiplied by the percentage of costs of goods sold attributable to labor costs. See Table 3 for remaining variable definitions. Coefficients on two-digit SIC code indicators are not reported.

* . **, *** indicate one-tailed statistical significance at the 10%, 5%, and 1% level respectively. Table reports coefficient estimates, and their corresponding *z*-statistics (z-statistics are reported in parentheses).

ENDNOTES

[1] 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 employees operating in the same physical location will naturally observe a variety of common signals concerning conditions of the plant in terms of temperature, humidity, availability of inputs such as raw material, etc. Because production employees share common observations, the cost of communicating each individual's unique information to other production employees will be significantly reduced. Conversely, because upper management cannot observe the common plant conditions, the cost of information sharing with management becomes prohibitive.

[2] Note that our assumption that ρ can be larger than k allows for the possibility that agents learn new information by working together. Therefore, ρ can be interpreted as capturing the increase in group-task related information stemming from the sharing and creation of knowledge when agents work together.

[3] We thank an anonymous reviewer for suggesting an information structure in which the information sharing model converges to the single signal model without information sharing as the information sharing parameter (ρ) approaches zero.

[4] There is no loss of generality in assuming in the model that salary is equal to zero.

[5] Agents can potentially use their specific knowledge to game performance measures. See Indjejikian and Matějka (2008) for further development of this argument.

[6] Allowing the principal to have perfect information on the two individual effort components makes the incentive weight placed on the individual output performance measure independent of the value of knowledge sharing. All other conclusions drawn from our analysis remain unchanged.

[7] Our results are robust to including these observations, which comprise 5.6% of the total sample.

[8] Because respondents report at the plant level and we do not have firm identifiers, it is possible that multiple manufacturing plants from the same firm are included in the survey.

[9] For a similar approach see Garvey and Milbourn (2000) and Ittner and Larcker (2002).

[10] These new technologies, for instance, enable employees to deal with unforeseen contingencies, which will require them to have an understanding of the logic of the equipment's internal functioning and information on the equipment's status (Adler and Borys 1996).

[11] We check the validity of our *NEW TECH* measure by examining the correlation of this measure with various other measures in our sample data that correspond to results reported in the Bureau of Census' SMT survey of Advanced Manufacturing Technologies. Consistent with *NEW TECH* being a reasonable measure of investment in advanced manufacturing technologies, we find significant positive correlation between *NEW TECH* and measures of Computer Aided Design (CAD), and Computer Integrated Manufacturing (CIM).

[12] We set *EMPOWERMENT* equal to 1, 2, 3, 4, 5, or 6 when respondents report that (1) 0%, (2) 1-25%, (3) 26-50%, (4) 51-75%, (5) 76-99%, or (6) 100%, respectively of the production workforce participates in empowered or self-directed teams.

[13] We check the validity of our *EMPOWERMENT* measure by examining the correlation of this measure with variables identified in the literature as being conducive to information sharing within organizations (e.g., Wruck and Jensen 1994; Cua, McKone and Schroeder 2001). Consistent with *EMPOWERMENT* being a reasonable proxy for information sharing, we find significant positive correlation between *EMPOWERMENT* and measures of the implementation of cross-functional and employee problem solving teams.

[14] Survey respondents categorized union representation at their plant as involving: (1) No workers (*UNION*=1); (2) Some workers (*UNION*=2); or (3) All workers (*UNION*=3).

[15] Survey respondents categorize their plant as having (1) less than 100 (*SIZE*=1); (2) 100-249 (*SIZE*=2); (3) 250-499 (*SIZE*=3); (4) 500-999 (*SIZE*=4); or (5) 1,000 or more (*SIZE*=5) employees.

[16] Survey respondents categorize the number of years since their plant's start-up as (1) less than 5 (*AGE*=1); (2) 5-10 (*AGE*=2); (3) 11-20 (*AGE*=3); or (4) More than 20 (*AGE*=4).

[17] Note that this implies that we drop two-digit SIC codes with less than 2 observations.

[18] We use the STATA program margeff developed by Bartus (2005) to compute average marginal effects.

[19] Categories for hours of annual training were (1) less than 8; (2) 8-20; (3) 21-40; and (4) more than 40 hours.

[20] If we instead use total training hours unadjusted for labor costs, the coefficient on total training hours is positive and significant for Hypothesis 1, but insignificant for Hypothesis 3 (all other findings remain supported). We conjecture that these weaker results for Hypothesis 3 are the result of a significant portion of total training for manufacturing workers being related less to employees' specific knowledge and more to the value of employee knowledge sharing (e.g., communications and quality training).