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Job Design, Learning & Intrinsic Motivation

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According to psychologists and neuroscientists, a key source of intrinsic motivation is learning. An economic model of this is presented. Learning may make work less onerous, or the employee may value it in and of itself. Multitasking generates learning: performing one task increases productivity on related tasks. Intrinsic motivation generates a new multitask incentive problem if the rate of learning varies across tasks. With no incentive pay, employee autonomy complements learning because expected output increases as the employee uses his or her knowledge to enhance learning. The second part of the paper adds a simple incentive. Incentive pay does not “crowd out” intrinsic motivation, but it does rebalance effort away from learning and towards output. Learning has complex interactions with performance measurement. A higher rate of learning tends to reduce performance measure distortion, especially for a very distorted measure. It also tends to reduce the potential for manipulation, as does multitasking. However, if job design is strongly imbalanced towards a few key tasks, or learning varies significantly across tasks, a higher rate of learning may increase the employee’s ability to manipulate the measure. In that case the firm might prefer an incentive with no autonomy, or autonomy with no incentive.

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1. Introduction

The study of agency problems is almost certainly the largest area of organizational / personnel economics, but the economic literature on intrinsic motivation is quite small. By contrast, the fields of organizational behavior and social psychology give significant emphasis to the topic. The purpose of this paper is to bridge this gap by developing a model of a particular type of intrinsic motivation that appears to be important, can be modified by firm policies, and meshes well with theoretical and empirical research in organizational economics.

The form analyzed here is intrinsic motivation driven by learning (broadly defined). Accumulating evidence from neuroscience indicates that learning is an important source of intrinsic motivation. Learning stems from attempting to address situations that are not fully understood. From birth, human brains react to new stimuli with curiosity, exploration, and attempts to resolve cognitive dissonance. This can have a powerful effect on behavior. In organizational behavior and social psychology, a related and influential literature considers how a firm might increase intrinsic motivation by using job design to foster learning. Work that involves variety, complexity, developing new skills, and problem solving may lead to stronger cognitive engagement – a significant form of intrinsic motivation.

If learning is an important cause of motivation at work, it is worthwhile to study how it interacts with other topics that we usually consider, including performance evaluation, incentives, and decision making. Moreover, effective use of knowledge, innovation and continuous improvement have been themes in economics for many years. Designing the job to increase the motivation to learn may be an important way to pursue these objectives.

In order to model the role of learning, two simple extensions are added to standard economic models, and implications for job design, motivation, performance evaluation and incentives are developed. The first is a model of how job design affects learning. When the job involves multiple related tasks, performing one improves the employee's ability to perform the others. Learning stemming from job design is of interest itself, but the second addition builds on this: to model intrinsic motivation from learning in two ways. First,

the employee may have lower disutility of effort if the job is more interesting. Second, the employee may personally value learning.

These effects motivate greater effort than would otherwise be provided, absent incentive pay, and partially align interests between the firm and the employee. However, if the rate of learning varies across tasks, a new type of multitask incentive problem emerges, as motivation is biased towards more learning-intensive tasks, while the firm cares about output.

Even though intrinsic motivation is not perfectly aligned with firm interests, in this model it increases total surplus because the employee's interest in learning has ancillary benefits for the firm. A similar result arises when we allow for a simple form of autonomy (decentralization). Autonomy allows the employee to become better informed, test ideas, and implement improvements. In the model presented here, granting autonomy to the employee increases surplus when there is no incentive pay.

In the second part of the paper, incentive pay is introduced. An additional contribution of the paper is to analyze the complex interactions between learning and performance measurement. Learning tends to improve alignment of the measure with output, especially if the measure is poorly aligned. Learning and multitasking also tend to make the performance measure more difficult to manipulate. However, learning may have the opposite effect if the job involves some dominant tasks with direct marginal productivity that is significantly higher than that of other tasks. In such a case, the employee learns how to better manipulate the measure. For these reasons, a higher rate of learning is likely to be associated with autonomy and stronger incentives only when performance measurement is reasonably effective, which in turn depends on job design. Autonomy may not be optimal in the presence of incentives if the performance measure is of poor quality, even though it is if there is no incentive.

The model provides a framework for analyzing interactions between job design, learning, performance evaluation, and incentives. Furthermore, it provides a way to study interactions between intrinsic and extrinsic motivation. Job design and learning have been studied in economics, but intrinsic motivation caused by learning adds a new element, and one that may be important in practice. Economists have emphasized the roles of decentralization and incentive pay to use employee knowledge more effectively, but

less often have considered how to design organizational policies to improve creation of that knowledge. Intrinsic motivation may be a key method by which firms can generate knowledge.

Intrinsic Motivation in Economics and Social Psychology

The term “intrinsic motivation” was coined by Harlow (1950), who observed that rhesus monkeys played puzzles even without rewards. Abstractly, it might be defined as any factor that affects the effort that a person devotes to an activity, other than a reward (monetary or otherwise) that is contingent on that effort or its result. Many examples have been considered, including pro-social behavior, enjoying the activity itself, and deriving a sense of meaning from its effects personally or for others. The topic is too large to survey here. The type of intrinsic motivation of interest in this paper has two characteristics. First, it is in a workplace context. Second, it is of practical relevance for the firm because policies can be used to increase such motivation. For example, employees might be motivated by a social enterprise’s mission. However, it is difficult for a firm to change its mission to motivate employees, since that would involve changing its product and strategy.

A small number of papers provide formal models of intrinsic motivation of employees. Murdock (2002) models a setting in which employees derive utility from a non-financial aspect of output (e.g., a social mission which firm activities might affect). Bénabou and Tirole (2003) provide a model in which incentives may affect motivation if they adversely affect an employee’s perception of his or her abilities in performing the task. Prendergast models intrinsic motivation caused by employee preferences over different aspects of performance, or for performing some tasks compared to others (2007, 2008, 2015). Cassar and Meier (2018) provide an overview of research on various ways in which work may provide a source of meaning (and therefore intrinsic motivation) for the employee, including mechanisms such as autonomy, feeling of competence, and feeling of relatedness to colleagues. Notably, while there is a large empirical literature on intrinsic motivation based on lab experiments, only a very small literature uses data from actual employment settings. For a history of this topic in economics, see Ramaniuc (2017).

Oudeyer, Gottlieb and Lopes (2016) review brain research on interactions between intrinsic motivation, curiosity, and learning. They state (p. 259) that “intrinsic motivation is clearly visible in young

infants.” This is driven by an interest in exploratory activities and a desire to resolve cognitive dissonance: “Novelty, surprise, intermediate complexity, and other related features that characterize informational properties of stimuli have ... been argued to be intrinsically rewarding, motivating organisms to actively search for them” (p. 258). In a survey of neuroscience research on intrinsic motivation, Di Domenico and Ryan (2017, p. 1) state that “intrinsically motivated exploratory and master behaviors are phylogenetically ancient tendencies that are subserved by dopaminergic systems.” In other words, intrinsic motivation stems from dopamine signals. Growing evidence finds that brain function changes when curiosity is engaged. Intrinsic motivation comes from “novel stimuli, namely, those that present optimal challenges or optimal inconsistencies with one’s extant knowledge ...” (p. 3). They also note that too little novelty tends to be boring, while too much produces anxiety.

While there are many ways in which scholars in social psychology and organizational behavior think about intrinsic motivation, one particularly influential approach considers how a firm can increase such motivation in its employees. The “Job Characteristics Model was designed to implement the idea that learning – and intrinsic motivation – can be stimulated by appropriate job design” (Hackman & Lawler 1971; Hackman & Oldham 1976; see Humphrey, Nahrgang & Morgeson 2007 for a meta-analysis of studies of this model). The model has long been a staple of organizational behavior courses and textbooks (e.g., see the best-selling OB text, Robbins & Judge 2019, ch. 8). It posits five job characteristics which may generate three psychological states leading to intrinsic motivation. Appendix A shows a graphical representation from Hackman and Oldham (1976); similar figures appear in many organizational behavior textbooks. The five characteristics (and one “moderator”) are:

Skill Variety: degree to which a job requires a variety of different activities.

Task Identity: degree to which the job involves a “whole” and identifiable piece of work.

Task Significance: degree to which the employees feels the job significantly affects others.

Autonomy: degree to which the employee is granted discretion.

Feedback: degree to which the job gives the employee information about performance.

Growth Need Strength: degree to which the employee has a “high need for personal growth and development.”

The idea is that intrinsic motivation can be generated by putting the employee into a challenging situation in which thinking and learning is required in order to resolve issues that are not understood, acquire new skills, and develop solutions to problems.¹ *Skill Variety* is implemented via multitasking (often called job “enrichment” or “enlargement”). *Autonomy* and *Feedback* support this by allowing the employee to experiment, gather evidence, and learn. Importantly, “effort” becomes more cognitive in nature, involving observation, diagnosis, hypothesis formation, and problem solving. An employee with higher *Growth Need Strength* is more intrinsically motivated by this cognitive challenge.

Despite its apparent importance, learning-driven intrinsic motivation has not yet been explored in economics. However, several of the job characteristics listed above are closely related to topics that economists study: multitasking, discretion (decentralization), and performance evaluation. Those are central elements of the model presented below.²

2. Basic Model

This section introduces the basic model. Production and performance evaluation are based on Holmstrom and Milgrom’s multitask incentive model (1991), and its adaptation by Feltham and Xie (1994). That is augmented with Lindbeck and Snower’s (2000) idea of intertask learning, which fits well with the emphasis placed on multitasking by psychologists. Employee utility adds elements to model intrinsic motivation. The model is static, though learning is dynamic. The goal is to lay tractable groundwork for thinking about these issues, and how they relate to key topics in organizational / personnel economics.

“Learning” should be interpreted broadly, and not limited to acquisition of human capital. The word is intended to capture various types of knowledge and information which an employee might create or observe in performing the job. One type might be acquisition of skills that apply to multiple tasks. Another comes from task complementarities. For example, research might improve a professor’s ability to teach a complex subject. Simultaneously, interaction with students might improve the choice of research topics or

¹ When Hackman (a former colleague) taught this topic to his PhD students, he would motivate it by stating that “humans are hardwired to learn,” using the example of a newborn infant.

² An interpretation of *Task Identity* will emerge from the model. Task Significance accords well with Murdock (2002), in which the employee gains utility from certain aspects of output. It will not play a role in our model.

generate ideas about how to make research progress. As a second example, a factory employee might be assigned to fashion one or both pieces of a machine that work together (e.g., a metal arm that moves an engine valve). By fashioning both, the employee better understands what is most important in shaping each piece so that they function together smoothly, such as the curvature of one edge, or the shape of a slot into which the other piece fits. This type of learning can be useful for improving product or service quality.

A further type of learning is acquisition of information about the stochastic work environment that may improve allocation of effort across tasks. For example, a jewelry store employee who greets new customers may be able to discern their mood, willingness-to-pay, and the special occasion for which they may be shopping. Such information is valuable for deciding which products to pitch, and for choosing the most effective selling technique for that customer.

Finally, performing a more complex job may stimulate creativity as the employee thinks more broadly, sees connections across different parts of the business, gains new perspectives, or abstracts lessons from one task and uses them to innovate elsewhere (Coelho and Augusto 2010).

Job Design

The employee exerts efforts e_i on $n \geq 2$ tasks, indexed with i , with production function Q :

$$Q = \sum t_i e_i = \sum (q_i + k l_i) e_i.$$

The marginal product of effort t_i has two components. The first is the direct effect on that task, q_i , with cross-task average $q = \sum q_i / n \geq 0$. The second is *intertask learning*, $l_i = l_i(q_{j \neq i})$. By working on one task, the employee learns and improves productivity on other tasks.³ The overall rate of learning is k . This is a simple way to parameterize environmental factors that affect opportunities for the employee to learn and improve operations. The task-specific component is $l_i \geq 0$, with average $l = \sum l_i / n$. Total learning is $L = \sum k l_i e_i$. Whether l_i varies across tasks or is constant will have important implications.

³ In principle the benefits of learning for other tasks would depend on efforts on those tasks. Such a model would be intractable. This approach is meant to capture cross-task interactions in a simpler way, particularly since the focus is on the effects of learning on motivation and performance measurement.

The direct marginal product q_i might be negative for some (but not all) tasks, but only if that is outweighed by learning benefits from performing such tasks, as the firm will not assign a task that reduces output; $t_i \geq 0$. For example, a plant manager might use a new manufacturing technique that increases quality problems, if the learning it generates outweighs this.

Learning

There are many ways to model intertask learning. The approach is inspired by Lindbeck and Snower's (2000) model of intertask learning; also see Gibbs, Levenson & Zoghi (2010). Most results follow for any vector l_i , but the two specific examples are used occasionally below because of their tractability.

The idea that performing one task may provide insights into how to better perform another task, and vice versa, suggests that l_i should be positively related to marginal products of other tasks, $q_{j \neq i}$. Of course, these interactions will depend on how many and which tasks are bundled together. They will also depend on the employee's skills, and resources that the firm provides (training, data, tools, etc.). Environmental uncertainty or change may increase benefits from learning. k is a simple way to parameterize these considerations as the overall rate of learning.

An important issue in what follows is the extent to which learning varies across tasks. It is useful to distinguish a simple case in which it does not vary, to highlight the role of such variation. There are two general types – neutral and non-neutral – which are described next, with simple examples for each.

Neutral: performing each task generates identical productivity improvements for all other tasks, $l_i = l$. With neutral learning, intrinsic motivation is not biased towards some tasks relative to others. An intuitive example is when learning is proportional to the average marginal product, $l_i = (n-1)q$. This term includes $n-1$ because learning improves performance on all other tasks. Total learning is $L = nk(n-1)q \sum e_i$.

Non-neutral: performing each task generates varying productivity improvements for other tasks. An intuitive example is when learning from one task improves productivity proportionally on other tasks, so that $l_i = \sum_{j \neq i} q_j = nq - q_i$, and $L = k \sum_i (nq - q_i) e_i$. The average is the same as in the neutral learning example, $\sum l_i / n = (n-1)q$, but learning varies across tasks. This will have important implications. Arguably, this is more realistic than neutral learning, but neutral is easier to work with and might suffice for some questions.

In both cases, l_i is stated in terms of average marginal productivity across tasks. If task i has relatively large marginal productivity q_i , it will have relatively small learning spillovers l_i (and vice versa), since that learning is applied to less productive tasks. This feature should apply to general models of inter-task learning. Finally, we assume that $l_i \geq 0$, because we are interested in productive learning. That is automatic in the two specific examples just described, if $q \geq 0$.

Utility

Employee utility is a familiar form, with three new elements to model intrinsic motivation:

$$Utility = \lambda L + E[Pay] - \frac{1}{2} r \sigma_{pay}^2 - \frac{1}{2} C(k, n) \sum (e_i - \underline{e})^2.$$

The employee enjoys utility from income, disutility from income risk with coefficient of absolute risk aversion r , and disutility of effort C . Effort on all tasks affects disutility symmetrically. This abstracts from intrinsic motivation driven by preference for some types of tasks compared to others (Prendergast 2007, 2008). Typically, the literature assumes that effort disutility is zero if efforts are zero. Instead, we follow Holmstrom and Milgrom's (1991) approach, in which disutility is a function of efforts net of some minimum amount $\underline{e} > 0$. This innocuous assumption is convenient for discussing intrinsic motivation, as the employee will provide some efforts without incentive pay. That is particularly appropriate in our context in which the employee values learning. Indeed, most people provide uncompensated effort in a variety of activities (hobbies, sports, reading good books) that involve learning.

Intrinsic motivation is modeled two ways. First, learning might make the work less onerous. We allow the rate of learning to affect C , with $\partial C / \partial k < 0$, $\partial^2 C / \partial k^2 > 0$, so that this occurs at a diminishing rate. This is consistent with Smith's (1776) observation that highly specialized, repetitive jobs (which presumably provide little opportunity for cognitive engagement) may be boring and demotivating. It is also consistent with the importance of *Skill Variety* in the Job Characteristics Model, and neuroscience research on causes of intrinsic motivation.

A second type of intrinsic motivation occurs if the employee values learning in and of itself, regardless of its value to the firm. For example, economists may enjoy new knowledge gained from research

or teaching, even if it provides no value to the university. This is modeled by assuming that the employee values learning with constant marginal utility λ . Diminishing marginal utility from learning would be more realistic, but this linear formulation is chosen for tractability, and in the interest of focusing on other issues.

The psychological concept of *Growth Need Strength* is captured by λ and $\partial C/\partial k$, as each measures an aspect of the employee's degree of intrinsic motivation from learning. This model provides two different ways to model intrinsic motivation from learning, because both seem plausible and potentially interesting. In what follows, it is straightforward to focus on only one mechanism or the other by setting λ to zero, or by assuming that C does not depend on k .

Aside from intrinsic motivation, multitasking might affect the disutility of effort. We allow C to be a function of n .

Profit & First-Best Effort

The firm is risk neutral and maximizes expected profit $Q - E(\text{Pay})$. Pay includes base salary S , and possibly a bonus. Total surplus equals expected profit plus utility, which nets out expected pay: $Q + \lambda L - \frac{1}{2}\sigma_{\text{pay}}^2 - \frac{1}{2}C\Sigma(e_i - \underline{e})^2$.

Holding efforts fixed, a higher rate of learning k increases employee utility, firm output, and thus total surplus. Several factors generate benefits from designing jobs to increase learning. It improves productivity, may benefit the employee, and may reduce the cost of effort. With this setup, first-best effort on each task maximizes total surplus:

$$\begin{aligned} \max_{e_i} \quad & Q + \lambda L - \frac{1}{2}rb^2\sigma^2 - \frac{1}{2}C \sum (e_i - \underline{e})^2 \\ (1) \quad & \Rightarrow e_i^s = \underline{e} + \frac{q_i + (1 + \lambda)kl_i}{C(k, n)}. \end{aligned}$$

The marginal benefits from extra effort include productivity on that task, learning benefits for other tasks, and the employee's utility from that learning, which are balanced against the disutility of effort. First-best effort rises with both types of intrinsic motivation (λ , $C(k)$). A reduction in the onerous of work due to

intrinsic motivation has greater value in jobs with higher marginal productivity. First-best effort also rises with the rate of learning.

3. Intrinsic Motivation

This section analyzes motivation in the absence of pay for performance. Consider the employee's utility-maximizing efforts if paid base salary S and no incentive:

$$\begin{aligned} \max_{e_i} \lambda \sum k l_i e_i + S - \frac{1}{2} C \sum (e_i - \underline{e})^2 \\ (2) \quad \Rightarrow e_i^* = \underline{e} + \frac{\lambda k l_i}{C(k, n)}. \end{aligned}$$

This provides several interesting insights. First, comparing (2) with (1), $\underline{e} < e_i^* < e_i^S$. This follows because $q_i + k l_i = t_i \geq 0$ or the firm would not assign the task. The employee provides efforts without an incentive, but they are less than first-best since he or she does not care about the value of output to the firm.

Second, both types of intrinsic motivation increase effort on all tasks. This is not surprising, of course. However, it is worth noting, as these effects are given prominence in psychology, but have received little attention in economics.

Third, if learning is non-neutral (l_i varies across tasks), either source of intrinsic motivation creates a new type of multitask incentive problem. Comparing (1) to (2), the employee allocates effort with a bias towards tasks that provide more learning. This is not caused by an innate employee preference for some tasks relative to others. It derives from valuing learning personally ($\lambda > 0$) and is reinforced if learning makes work less onerous. As mentioned above, non-neutral learning seems more realistic than neutral, in which case this multitask issue will be present.

This indicates that intrinsic motivation from learning is not necessarily an unmitigated good. It may generate a conflict of interest between the employee and the firm. Clearly incentive pay can play a role, as will be discussed below.

Multitasking

Leaving intrinsic motivation aside, briefly consider multitasking. For convenience, treat the number of tasks as continuous, though it is an integer. The effect of n on effort is ambiguous:

$$\frac{\partial e_i^*}{\partial n} = \frac{\lambda k}{C} \frac{\partial l_i}{\partial n} - \frac{\lambda k l_i}{C^2} \frac{\partial C}{\partial n} \gtrless 0.$$

Both terms might be positive for low n but may become negative if n is large. With respect to the first term, much research suggests that multitasking fosters learning, so we might assume that $\partial l_i / \partial n > 0$. That is the case for the two examples of l_i given above. However, learning benefits may dissipate or turn negative if the employee has to perform too many tasks, if for no other reason than too much time will be spent switching between tasks. With respect to the second term, an employee may enjoy some multitasking, but cognitive overload is likely to set in if n is large enough, with $\partial C / \partial n > 0$. Hackman and Oldham note that if a job is too complex, it can be highly stressful; this is why they introduced the concept of *Growth Need Strength*. Empirical studies find that productivity initially rises, but eventually declines, with the number of tasks (e.g., Aral, Brynjolfsson & Van Alstyne 2012). These arguments suggest a psychological cost to large levels of multitasking, to balance against learning benefits.

Autonomy

Autonomy is a component of the Job Characteristics Model. Hackman and Lawler (1971, p. 263) state, “In jobs high on measured autonomy, employees will tend to feel that they own the outcomes of their work; in jobs low on autonomy, an employee may more often feel that successes and failures on the job are more often due to the good work (or to the incompetence) of other employees or of his supervisor.” This might be interpreted as suggesting that employees value autonomy in itself, but that is not clear. It is plausible that people prefer discretion over how they perform their work, if for no other reason than to reduce risk imposed on them by the whims of the supervisor. However, we follow the approach of the economics literature, treating autonomy as decentralization rather than an additional component of the utility function.

A job has more autonomy if the employee is granted more decision rights over how to perform the work. *Autonomy* and *Feedback* are complementary. Autonomy allows the employee to generate more ideas,

develop hypotheses about causes and methods, and experiment. Feedback provides data to test those ideas and measure outcomes (Wruck & Jensen 1994). It is interesting to note that when firms implement job designs using these techniques, employees are often expected to collect and evaluate their own data. That clearly suggests that feedback has roles other than performance measurement for monitoring and incentives. Thinking about what to measure, how to collect the data, and how to interpret it are important ways in which an employee becomes engaged in learning – akin to assigning problem sets to students.

Use of autonomy (decentralization) when the employee possesses “specific knowledge” (knowledge that is costly to communicate to a centralized decision maker) is an important theme in the economics literature (Jensen & Meckling 1992; Holmstrom & Milgrom 1995; Prendergast 2002). That seems particularly relevant in our context. On-the-job learning may be complex, intangible, or perishable (more valuable if acted upon quickly) – all of which would make it more costly to communicate to a supervisor (Lazear & Gibbs 2015).

To consider this issue, assume that the rate of learning is stochastic, $E\tilde{k} = \bar{k}$. Further assume that $E\tilde{\epsilon}_t \geq 0$. The firm does not observe $\tilde{k}$. If it centralizes decision making, the employee chooses optimal efforts without observing $\tilde{k}$. If it decentralizes, the employee is granted autonomy, observes $\tilde{k}$, and then chooses optimal efforts.⁴ In that case incentive pay generates a new type of income risk, because marginal products of effort on the performance measure are stochastic (see below). This is intractable since income risk depends on effort levels and is no longer additive. There is also *effort risk*, as the disutility of effort varies with $\tilde{k}$. Effort risk aversion seems to be an interesting topic for empirical research, and to my knowledge has not been studied, but it is beyond the scope of this paper. For these reasons, discussions of autonomy (including when incentive pay is added below) assume that the employee is risk neutral.⁵

The firm and employee first negotiate terms of the job (possibly including incentive pay). Salary S may differ between the cases of withholding or granting autonomy. However, it has no effect on decisions

⁴ This can be considered a new task: collecting and analyzing information about the state of the world, prior to allocating effort.

⁵ Disutility of effort does have a risk aversion effect in this model. In the no autonomy case, disutility of effort is random, even though the employee chooses efforts, and it is convex in efforts.

at the margin, and nets out of total surplus. At that stage the employee will not know k , so for the purposes of maximizing total surplus, we must consider ex ante expected utility, conditional on ex post setting of efforts with or without knowledge of k . Denoting random variables with tildes and expected values with bars (e.g., $\tilde{t}, \bar{C}$):

$$\begin{aligned}
 \text{Expected total surplus} &= E(\text{Output}) + E(\text{Utility}) \\
 (3) \quad &= E \left\{ \sum \tilde{t}_i e_i^* + \lambda \tilde{k} \sum l_i e_i^* - \frac{1}{2} C(\tilde{k}) \sum (e_i^* - \underline{e})^2 \right\}.
 \end{aligned}$$

With autonomy, effort e_i^A is chosen with knowledge of k , so it is as in (2). Without autonomy, effort e_i^N is chosen to maximize expected utility with stochastic $\tilde{k}$ and $C(\tilde{k})$. Denoting $\bar{C} = C(\bar{k})$,

$$\begin{aligned}
 \max_{e_i} E \left\{ \sum \lambda \tilde{k} l_i e_i + S - \frac{1}{2} C(\tilde{k}) \sum (e_i - \underline{e})^2 \right\} \\
 (4) \quad \Rightarrow e_i^N = \underline{e} + \frac{\lambda \bar{k} l_i}{\bar{C}}.
 \end{aligned}$$

Which approach is preferred? Granting autonomy makes the employee better off, since he or she maximizes expected utility with knowledge of k instead of without. Any effort choices that would be made with centralization could also be made with decentralization, but the choices can probably be improved with knowledge of k .

Might the employee use knowledge of k strategically for private benefit at the expense of the firm? In this model that is not the case. Optimal efforts with autonomy are the same as in the full-information case in (2), which are below first-best levels. Actual efforts with autonomy will be above or below efforts with no autonomy, as the employee reacts to variation in the rate of learning k . That has a linear effect on learning and output, but a nonlinear effect on the disutility of effort. For this reason, uncertainty about the rate of learning moves efforts further from first-best levels:

$$E e_i^A - E e_i^N = \lambda \sum l_i \left(E \left(\frac{k}{\tilde{C}} \right) - \left(\frac{\bar{k}}{\bar{C}} \right) \right) \geq 0.$$

Similarly, expected output is higher with autonomy Q^A than without:

$$E Q^A - E Q^N = E \sum (q_i + \tilde{k} l_i) (e_i^A - e_i^N)$$

$$= \lambda \sum q_i l_i \left(E \left(\frac{k}{\bar{c}} \right) - \left(\frac{\bar{k}}{\bar{c}} \right) \right) + \lambda \sum l_i^2 \left(E \left(\frac{k^2}{\bar{c}} \right) - \left(\frac{\bar{k}^2}{\bar{c}} \right) \right) \geq 0.$$

These two results follow from Jensen's Inequality, since $1/C$, k/C and k^2/C are convex in k .

With autonomy the employee uses knowledge of k to maximize utility, but this also benefits the firm. Efforts increase when k is high, and vice versa, traded off against variation in the marginal cost of effort. This has the side effect (from the employee's perspective) of increasing expected output, because effort is allocated more efficiently as k varies, and there is higher average effort. Intuitively, these differences in expected efforts and output should generally rise with an increase in variance in k . Information then has greater value, so autonomy is more useful.

Since both the employee and the firm are better off, autonomy is preferred to centralization in this model. Though the modeling of uncertainty is simplistic, it illustrates the idea that autonomy complements learning by helping the employee to better allocate efforts to tasks which currently provide more opportunities to learn. This may be viewed as a special case of Prendergast's (2002) argument that delegation may be optimal when the work environment is uncertain. The opportunity to learn and improve productivity is a particular form of uncertainty. Variation in that opportunity is another. In a dynamic model, feedback, including subjective performance evaluation and coaching, would reinforce this result.

Summing up this section, we modeled intrinsic motivation generated by on-the-job learning. If the job is designed so that the learning also improves productivity, the firm benefits, and intrinsic motivation generates some alignment of interests between the firm and the employee. However, the alignment is not perfect since the employee cares about learning but not the economic value of output. Moreover, unless learning is neutral, it creates a multitask incentive problem, as the employee puts too much weight on tasks that offer learning instead of direct productivity. We also showed that autonomy complements learning by providing the employee with greater flexibility to adapt to the changing work environment. With this base established, the next section analyzes how these issues interact with performance evaluation and incentives.

4. Extrinsic and Intrinsic Motivation

We described two roles for employee feedback: providing information which can be used to better allocate efforts, and providing evidence to test hypotheses and improve learning. A third is performance evaluation: coaching and training, monitoring, or to tie to rewards. The latter role is the topic of this section.

Performance Measurement

The firm offers a linear bonus with incentive intensity b . Output is assumed to be non-contractable, so it uses performance measure P to proxy for Q :

$$P = \sum m_i e_i + \tilde{\varepsilon} = \sum_{i=1}^n (p_i + k v_i) e_i + \tilde{\varepsilon}.$$

Measurement error $\tilde{\varepsilon}$ has variance σ^2 ; therefore, $\sigma_{P_{ay}}^2 = b^2 \sigma^2$. The marginal effect of effort e_i on the evaluation depends on its direct effect on the measure, p_i . Since learning affects performance, we model it as affecting evaluation of performance in a similar way, $k v_i$. Define the average values as $p = \Sigma p_i / n$, $v = \Sigma v_i / n$.

The literature on performance measurement (primarily in accounting research) highlights two key properties that are of interest in this model: the potential for manipulation, and the extent to which the measure distorts multitask incentives. Learning affects both.⁶

Manipulation

For production, we assumed that $t_i \geq 0$ or the task would not be assigned. By contrast, it is conceivable that $m_i < 0$ for some task. Reducing effort on such a task would lower output but raise measured performance. For this reason, we say that a task is *manipulable* if $m_i < 0$. This might occur if $p_i < 0$, $l_i < 0$, or both. If $v_i < 0$, this is a new form of manipulation, *counter-productive learning*. Increasing effort on this task might allow the employee to improve measured performance with lower effort on other tasks. In effect, the employee learns how to manipulate evaluation of other tasks. For example, a CFO who devotes effort to understanding the timing of revenue and cost recognition may learn how to manipulate earnings more

⁶ A third important property of performance measures is noise, σ^2 . That topic is avoided in this model as noise is assumed to be exogenous. In practice, it is likely that it will be larger in environments in which learning is more extensive. If the firm already understands the production environment very well, it is likely to have developed more accurate methods of measuring performance, and vice versa.

effectively. For a sensible performance measure such effects should average out across all tasks, so assume that $\Sigma p_i \geq 0$ and $\Sigma v_i \geq 0$; thus $\Sigma m_i, p, v \geq 0$.

Learning can make manipulation more or less likely, depending on whether it is productive or counter-productive ($v_j < 0$). First assume that all learning effects are productive so that $v_i > 0$ for all tasks (which is the case for neutral learning). If so, the condition for a task to be manipulable is more restrictive: $p_j < -kv_j < 0$. Any temptation for an employee to manipulate performance by reducing effort on a task is mitigated by beneficial performance measure spillovers to other tasks. In such a case, p_j would have to be relatively large in absolute value, suggesting that manipulation is more likely in jobs that are less balanced across tasks. If learning is non-neutral and counter-productive on some task j , this reduces m_j , potentially to become negative. Once again, imbalance across tasks ($v_j < 0$ and large in absolute value compared to $v_{i \neq j}$) makes manipulation more plausible.

Multitasking should reduce the likelihood of manipulation, since the negative effects of one task must overcome the positive effects of a greater number of other tasks. For example, in the non-neutral learning example described above, $v_i = (np - p_i)$. As n rises this is less likely to be negative. This effect, and the observation that “balanced” performance measures are less manipulable, are consistent with the idea that broader performance measures (covering more underlying components) are more difficult to manipulate (Lazear and Gibbs 2015, ch. 9).

While such perverse effects of learning are possible, a firm will try to avoid adopting highly problematic performance measures. If manipulation is significant, the firm has three options. It can reduce the incentive weight for that measure (see (9) below). It can redesign the job so that measurement is less problematic. Or it can eliminate incentive pay and rely on intrinsic motivation.

Distortion

An important issue with multitasking is distortion of the performance measure to the extent that marginal effects of effort on the measure are not well aligned with their marginal effects on output (Holmstrom & Milgrom 1991; Feltham & Xie 1994). A useful way to measure this concept is the cosine of

the angle θ between the vectors t_i and m_i of marginal effects of effort on output and the performance measure (Baker 2002). A lower value means that the measure is more distorted:

$$(5) \quad \cos\theta = \frac{\sum t_i m_i}{TM}.$$

T and M are the lengths of those vectors. Dividing by them normalizes and allows for consideration of distortion independent of the scaling of P and Q (both of which change with a change in k , usually by different magnitudes). If $P = Q$, $\cos\theta = 1$.

As with manipulation, the effect of learning on performance measure distortion is complex:

$$(6) \quad \frac{\partial \cos\theta}{\partial k} = \left(\left(\frac{V}{M} \right) \cos_{tv} + \left(\frac{L}{T} \right) \cos_{ml} \right) - \cos\theta \left(\left(\frac{L}{T} \right) \cos_{tl} + \left(\frac{V}{M} \right) \cos_{mv} \right),$$

where $\cos_{xy}$ is the cosine of the angle between vectors x_i and y_i (see Appendix B). The effect of increased learning on distortion depends on how well elements of the measure (p_i, v_i) align across tasks with elements of the production function (q_i, l_i). As k rises, the employee is motivated to increase efforts (except on tasks for which $v_i < 0$). If learning effects on the measure align relatively well across tasks with its effects on output ($\cos_{tv}$), increased learning tends to reduce distortion. If instead they align more with the measure ($\cos_{mv}$), more learning tends to increase distortion. Similarly, learning reduces distortion if its effects on output align well across tasks with its effects on the measure ($\cos_{ml}$). If instead they align more with total output ($\cos_{tl}$), learning tends to increase distortion.

The fact that $\cos\theta < 1$ imparts a tendency for the effect of k on distortion to be positive in (6). The more distorted the measure ($\cos\theta$ closer to 0), the more that is likely. If the measure has relatively low distortion ($\cos\theta$ closer to 1), general statements about the effect of an increase in k are not easy in the case of non-neutral learning. For neutral learning, it is possible to draw an intuitive conclusion. If the measure gives more weight to learning than does the production function, a rise in the rate of learning will increase distortion unless it is counterbalanced by the production function having a larger overall marginal product (and vice versa). See Appendix B for details.

Counter-productive learning ($v_i < 0$) may worsen distortion. That seems especially likely if manipulation is caused by $v_j < 0$, so that the employee learns how to better manipulate the measure. This interesting issue is beyond the scope of this paper.

It has been observed that performance measures may degrade in usefulness over time (Courty & Marschke 2003, 2008). Learning provides one potential explanation.⁷ First, it might increase distortion between the measure and output. Second, the employee may learn how to better manipulate the measure.

Optimal Incentive

For given b , the employee's effort to maximize expected utility is:

$$\begin{aligned} \max_{e_i} \quad & \lambda L + bP - \frac{1}{2}rb^2\sigma^2 - \frac{1}{2}C \sum (e_i - \underline{e})^2 \\ (7) \quad & \Rightarrow e_i^* = \underline{e} + \frac{\lambda kl_i + bm_i}{C(k, n)}. \end{aligned}$$

For non-manipulable tasks, effort will be larger than if there is only intrinsic motivation, and will increase if the incentive intensity is raised:

$$(8) \quad \frac{\partial e_i^*}{\partial b} = \frac{m_i}{C}.$$

Both statements are reversed for manipulable tasks. The firm sets the incentive intensity to maximize total surplus, subject to (7). Doing so and substituting in (7) and (8) yields:

$$\begin{aligned} \max_b \quad & Q + \lambda L - \frac{1}{2}rb^2\sigma^2 - \frac{1}{2}C \sum (e_i - \underline{e})^2 \\ \Rightarrow \quad & \sum t_i \frac{\partial e_i^*}{\partial b} + \lambda \sum kl_i \frac{\partial e_i^*}{\partial b} - rb\sigma^2 - C \sum (e_i - \underline{e}) \frac{\partial e_i^*}{\partial b} = 0 \\ \Rightarrow \quad & \frac{1}{C} \sum t_i m_i + \frac{\lambda}{C} \sum kl_i m_i - rb\sigma^2 - \frac{1}{C} \sum (\lambda kl_i + bm_i) m_i = 0 \\ (9) \quad & \Rightarrow b^* = \frac{\sum t_i m_i}{\sum m_i^2 + r\sigma^2 C(k, n)} = \frac{TM \cos \theta}{M^2 + r\sigma^2 C(k, n)}. \end{aligned}$$

⁷ Another explanation is that the environment changes, so the performance measure should evolve.

Expression (9) is a familiar term in the literature. It exhibits a key purpose of incentive pay in this model: rebalancing incentives towards direct marginal productivity q_i relative to learning l_i , since intrinsic motivation is biased towards learning. This works well to the extent that m_i is reasonably aligned with t_i . Furthermore, if a task is manipulable, it reduces the optimal incentive. In (9) manipulation would be reflected in an increase in M , because manipulation requires relatively imbalanced measures in which one or more tasks have negative p_i and / or v_i that are relatively large in absolute value. It would also be reflected as a reduction in $\cos\theta$ since some components of M would be negative.

The optimal incentive intensity is the same whether or not the employee values learning itself ($\lambda > 0$), since that generates personal utility. The incentive is used to motivation additional interest in the firm's value from learning. The optimal incentive does depend on the second form of intrinsic motivation, as k affects C . If learning reduces the marginal disutility of effort, the optimal incentive intensity will be larger.

Effect of Learning on Incentives

Since learning raises output for fixed levels of efforts, it is tempting to conclude that a higher rate of learning implies a larger optimal incentive intensity. However, this is not necessarily the case. There are three effects, two of which work in that direction, but one of which works against the conclusion. First, learning increases marginal products, so there is more value to an incentive. Second, it reduces the marginal disutility of effort, which increases b by lowering the marginal cost of eliciting effort. Third, learning might increase manipulation or distortion, which would work in the other direction.

We argued above that firms will tend to design jobs and choose performance measures so that their flaws are not too significant. To the extent that this is true, we should expect the incentive intensity to be larger in a job with greater opportunities for learning, *ceteris paribus*. That corresponds well with available empirical evidence (Ortega 2009; DeVaro & Kurtulus 2010).

Autonomy & Incentives

We showed above that autonomy is always optimal if there is no incentive because expected output and utility rise. Does the same conclusion apply once we add pay for performance?

The optimal incentive intensity can be derived with or without autonomy by maximizing expected total surplus subject to the employee's optimal effort choices (ignoring risk aversion as previously, since $\tilde{k}$ is stochastic). With autonomy, e_i^A is as in (7). With no autonomy, e_i^N is similar to (4), with a new term reflecting the incentive:

$$e_i^N = \underline{e} + \frac{\lambda l_i \bar{k}}{\bar{C}} + \frac{b \bar{m}_i}{\bar{C}}.$$

The procedure that was used to derive (9) yields the optimal incentive intensity with or without autonomy. First consider the incentive with no autonomy:

$$b^N = \frac{\sum \bar{t}_i \bar{m}_i}{\sum \bar{m}_i^2} = \frac{\bar{T}}{\bar{M}} \cos_{\bar{t}_i, \bar{m}_i}.$$

In effect, the performance measure is $\bar{P} = \sum \bar{m}_i e_i$, and the employee is motivated by the effect of efforts on expected output $\bar{Q} = \sum \bar{t}_i e_i$. Distortion of this measure is $\cos_{\bar{t}_i, \bar{m}_i}$, which b^N rescales to the extent that $\bar{M} \neq \bar{T}$.⁸ Use of an incentive will increase expected total surplus in the case with no autonomy, because it better aligns the employee's interests with those of the firm. This can be shown by a straightforward extension of the proof that expected total surplus rises with autonomy in the no incentive case, in which effect of the incentive on effort is included.

With autonomy, the optimal incentive is:

$$(10) \quad b^A = \frac{E \sum t_i m_i}{E \sum m_i^2} = \frac{\sum \bar{t}_i \bar{m}_i + \sum \text{cov}_{t_i, m_i}}{\sum \bar{m}_i^2 + \sum \sigma_{m_i}^2} = \frac{\sum \bar{t}_i \bar{m}_i + \sigma_k^2 \sum l_i v_i}{\sum \bar{m}_i^2 + \sigma_k^2 \sum v_i^2}.$$

The intermediate step follows because $E(xy) = \text{cov}(x, y) + \bar{x}\bar{y}$ for any x, y . The final step follows from the definitions of t_i and m_i .

When the firm grants autonomy, it sets a fixed incentive intensity ex ante, but the employee observes k before choosing efforts. Performance measure distortion is *random* from the firm's perspective. For values of k that align m well with t , it would like to set a high incentive, and vice versa. The optimal incentive intensity equals the average inner product of these vectors, rescaled by the average length of the

⁸ Even if the firm rescales P so that $M = T$, it is likely that $\bar{M} \neq \bar{T}$ because the average learning effects v and l may be different.

performance measure vector. Since t and m vary with l and v as the rate of learning varies, b^4 will be larger to the extent that l and v are well aligned and vice versa. This is seen in the last terms in the numerator and denominator in (10).

Derivations of optimal incentives assume interior solutions, but those are not guaranteed, in which case the optimal incentive might be zero. Once again, the conclusion depends on how the quality of the performance measure varies with the extent of learning. If learning improves the evaluation, incentives should rise with autonomy. If it does not, then granting autonomy generates a second form of manipulation in which the employee uses knowledge of k to vary effort in ways that increase the evaluation more than output. If the performance measure is significantly flawed, it is conceivable that expected total surplus might be lower with the incentive than without. If that is the case, the firm might withhold autonomy and use an incentive, or grant autonomy with no incentive.

“Crowding Out” of Intrinsic Motivation

One of the most contentious debates between organizational psychologists and economists involves the claim that incentive pay might “crowd out” intrinsic motivation (Deci 1971; Frey 1997). This model provides little support for that view. To the contrary, incentives may complement intrinsic motivation.

First, in this model incentive pay does not reduce the employee’s utility from learning itself, nor the level of intrinsic motivation. Employees value pay but also value a job in which they learn. There seems little reason to assume that these are substitutes or complements in utility. Second, incentive pay does not eliminate the reduction of effort disutility deriving from intrinsic motivation. In fact, that effect makes incentive pay *more* effective, since it reduces the marginal cost of eliciting greater effort. Third, learning will tend to make well-behaved performance measures more effective. Furthermore, we may well find a positive correlation between incentive pay and measures of employee *Growth Need Strength*.

That said, optimal incentive pay should be designed to rebalance motivation, which may be intrinsically biased towards learning rather than output. It should not be surprising to observe that incentive pay changes the worker’s focus away from “creative” tasks. However, in this model that is optimal, and it does not have a fundamental psychological cause.

Our analysis also indicates that learning may worsen the effectiveness of the performance measure. It may distort incentives further towards learning instead of general productivity. To the extent that is the case, learning arguably “crowds in” intrinsic motivation. More subtly, learning may be counterproductive, so that the employee is improving his or her ability to manipulate the performance measure. That is an additional sense in which incentives may redirect the focus of the employee’s effort away from outcomes usually associated with intrinsic motivation.

5. Discussion

The final point in the previous section begs broader questions of optimal job design and performance evaluation. I provide brief remarks on potential extensions before concluding.

The question of how to design a job to foster learning is interesting. The simple intertask learning approach taken here could be modified or extended in several ways. A deeper model might consider the optimal bundling of tasks based on complementarities in production, skill requirements, or knowledge sharing. One likely outcome of such an effort would be that the firm will exploit modularity in the business process. To the extent that steps in the process can be bundled into relatively separable modules (with significantly lower task coordination costs with than between modules), jobs would be designed as a set of tasks within a module to maximize intertask learning. This provides an economic interpretation of Hackman and Oldham’s job characteristic *Task Identity*.

It would be more realistic to model learning with a multiperiod approach. This would facilitate consideration of accumulation of knowledge, as well as evolution techniques, job design, and performance measurement. The latter could allow analysis of *Feedback* as coaching for training rather than evaluation for incentives. It might also facilitate consideration of relational contracting, in which the employee and firm work in a Coasian partnership to create and use knowledge.

Team production is an important consideration that was ignored. Teams generate coordination and agency costs but might also aid learning. They allow the firm to “expand the size of the job” beyond the number of tasks that is optimal for one person, in order to achieve better *Task Identity*. A team would be

defined as a group of employees assigned to work together towards producing a modular subset of tasks (e.g., fashioning and assembling the transmission in an automobile factory). Each team member specializes in some set of tasks, but with the additional task of collaborating closely with teammates. Some understanding of the work performed by teammates is required for effective coordination. Job rotation might gradually provide each teammate with better understanding of the entire module while still enjoying some benefits from specialization. Teams also expand the portfolio of knowledge, experiences, and perspectives available. This can improve problem-solving, and diversity of perspectives may stimulate creativity.

A decentralized, employee-focused approach to learning is not the only method that organizations employ (Lindbeck & Snower 2000; Gibbs, Levenson & Zoghi 2010). In many cases, perhaps most, firms use experts who develop and implement best practices. Once best practices are understood, employees are trained and expected to perform those with close adherence to proscribed methods – there is little autonomy. Otherwise employees might “innovate” in ways that are less effective than best practices. If centralized learning works well, multitasking to foster learning is not needed so jobs can be specialized. Therefore a focus on intrinsic motivation in recruiting, job design and performance evaluation should be most important in situations where the firm has more to learn: the product or process is complex, the environment is changing, or it is unpredictable.

An illustration of this idea is Caroli and van Reenen’s (2001) evidence on how job designs changed when firms went through large-scale organizational changes. An organization that went through major restructuring is likely to have significant opportunities for learning, because they are using different methods than before, and in many cases face an operating environment that has changed from the past. After the restructuring, employees reported that they had to perform a much wider range of tasks, were given greater responsibility (autonomy), and were expected to develop higher skill levels. Notably, they also reported that their jobs were significantly more interesting (64% more in non-manual jobs and 37% in manual jobs). Caroli and van Reenen interpreted their findings as evidence for skill-biased organizational change. It seems reasonable to also interpret their findings as evidence for intrinsic motivation-biased organizational change.

The model revealed complex interactions between learning and performance evaluation. The approach to evaluation modeled in this paper was simplistic and could be expanded in several ways. First, it would be interesting to more fully develop how job design and learning affect performance measures and their properties. This might include insights into how to choose effective measures to reinforce intrinsic motivation, learning and alignment with firm objectives. Second, evaluation is much richer in practice. Firms can adopt multiple measures and use different types of incentives. Subjective evaluation is especially important. In a job with significant learning, it may be difficult to clearly specify metrics and goals *ex ante*. Moreover, many employee insights will be complex and intangible, and so will require judgment by the evaluator. The job will evolve, so the evaluation should also evolve, and effective relational contracting for subjective evaluation will make that easier. Moreover, the supervisor can give more emphasis to coaching, training, and feedback, rather than monitoring and measurement. Finally, empirical analyses of these issues will need to take into account that noise in performance measures is not likely to be exogenous as assumed here, but rather it is likely to be negatively correlated with opportunities for learning on the job. That point is very similar to Prendergast's (2002) discussion of the tenuous tradeoff between risk (noise) and incentives, and the work which built on it (Ortega 2009; DeVaro & Kurtulus 2010).

Employees differ in the extent of their intrinsic motivation. The role of this employee characteristic in the labor market is interesting. There has been a trend towards organizational designs that foster learning and continuous improvement, driven by technological change, increased competition, and international trade. This suggests that an interest in learning is a factor that firms should consider in recruiting, especially in complex jobs involving cognitive tasks. It would be interesting to measure how the labor market values employees with high *Growth Need Strength*, and how that might have changed over time.

6. Conclusions

Humans are hardwired to learn. Organizational economists have shown increasing interest in policies that foster learning, continuous improvement, and innovation (Ichniowski, Shaw and Prennushi 1997; Ichniowski and Shaw 2003). They have devoted enormous effort to understanding extrinsic motivation, but

have paid little attention to intrinsic motivation. Social psychologists have long treated intrinsic motivation as a central issue. They argue that learning is an important source, and this is well supported by neuroscience research. This paper has attempted to bring this type of intrinsic motivation into economic analysis. Organizational learning is often studied technically (job design, skills, resources, etc.) and economically (decentralization to use the employee's specific knowledge, complementarity of HR policies, etc.). However, economists have overlooked a potentially important motivational component. Including intrinsic motivation should improve our understanding of how organizations can create and use knowledge effectively.

The model extends standard economic models in two ways. First, production is augmented to include intertask learning. Multitasking fits well with what we know from psychology, neuroscience, and empirical evidence on how organizations design policies to foster learning. When an employee is assigned tasks that are complementary, such learning may occur (Deore, Holzhacker & Krishnan 2021). Many tasks must be coordinated with each other to complete a business process. Specialization can raise quality problems when complementary tasks are given to separate employees. Ideas about improvements to one task may come from a broader understanding of how that task relates to other parts of the process. Environmental risk and change are likely to be correlated across related tasks, so that an employee's information might be more broadly applied with multitasking. Finally, many tasks have related skills.

The second innovation of the model is to add learning-driven intrinsic motivation to the employee's utility function. Employees may value learning intrinsically. If so, they will work harder in jobs with such opportunities. In addition, work may be more interesting if it involves learning. This partially aligns interests. Any professor should find both ideas plausible.

A simple form of autonomy was considered. In this model it is optimal to grant autonomy in the absence of incentive pay, because the employee's enjoyment of learning provides partial alignment with firm interests, so that information is used for mutual benefit.

The second type of intrinsic motivation, lower marginal disutility of effort in the presence of learning, seems too simple to be of interest.⁹ However, if learning is non-neutral across tasks, it generates a new

⁹ Murdock 2002.

type of multitask incentive problem, as the worker becomes biased towards learning-intensive tasks, regardless of their contribution to economic value. Neutral learning is tractable, but the idea that rates of learning should vary across tasks is more realistic, so this problem seems likely to be relevant in practice.

This complication suggests a role for incentive pay in rebalancing motivation from learning towards output. The second half of the paper considered a simple linear bonus on a single numeric performance measure. A number of interesting complications arise when learning affects the employee's evaluation. It might cause greater distortion or manipulation of the measure. While it was not possible to derive specific conditions under which this might occur, several reasons were provided to suggest that, for reasonably effective measures, learning will tend to better align interests and reduce the potential for manipulation. These are interesting empirical questions.

It is hoped that this paper will motivate economists to give more attention to intrinsic motivation, theoretically and empirically. More could be done on modeling job and organizational designs that foster learning, and trade that off against the benefits of specialization and coordination. Similarly, it should be possible to make progress in understanding how learning affects performance measurement. That topic could be extended to consider multiple measures, subjective evaluation, and supervisor coaching / feedback. Most importantly, all of these topics seem incomplete without consideration of intrinsic motivation.

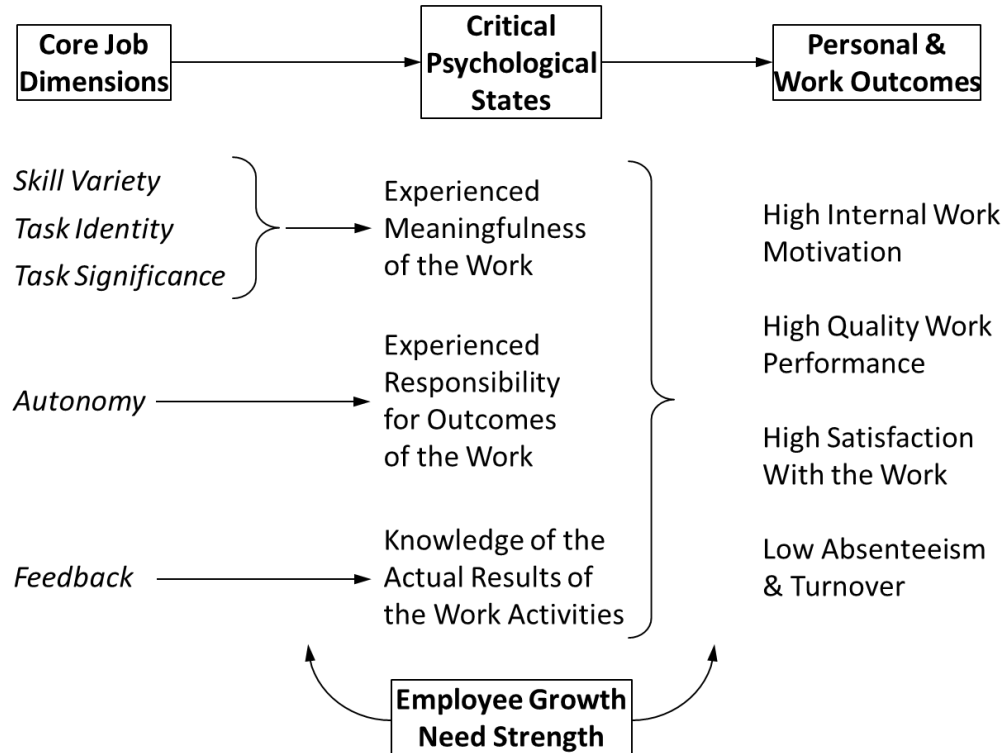
All of these issues are ripe for empirical research. Also of interest would measuring intrinsic motivation, or its effects on behavior or work outcomes (e.g., Kolstad 2013; Gibbs, Neckermann & Siemroth 2017). Are both types of learning-based intrinsic motivation empirically relevant? If measures of, or proxies for, *Growth Need Strength* can be obtained, it will be possible to study how they vary across occupations, types of jobs, the extent to which work involves cognitive tasks, etc. Finally, there is great interest in how labor market demand for employee characteristics such as cognitive and social skills are evolving with technological change (Deming 2017; Autor 2019). It would be of similar interest to understand how supply and demand for employees with preferences for learning plays out in the labor market.

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Appendix A: Hackman-Oldham Model of Intrinsic Motivation



Source: Hackman & Oldham (1976), Figure 1.

Appendix B: Effect of Learning on Performance Measure Distortion

In this appendix, vectors are in **bold**. Use inner product notation, e.g., $\mathbf{t} \cdot \mathbf{m} = \sum_i t_i m_i$. Vector lengths are capitals, e.g., $T = (\mathbf{t} \cdot \mathbf{t})^{1/2}$.

$$\frac{\partial T}{\partial k} = \frac{1}{2}(\mathbf{t} \cdot \mathbf{t})^{-1/2}(2\mathbf{t} \cdot \mathbf{l}) = \frac{\mathbf{t} \cdot \mathbf{l}}{T},$$

and similarly for M . Distortion is $\cos\theta = \mathbf{t} \cdot \mathbf{m} / TM \leq 1$, larger values mean lower distortion.

$$\begin{aligned} \frac{\partial \cos\theta}{\partial k} &= \frac{1}{TM} \left(\frac{\partial \mathbf{t} \cdot \mathbf{m}}{\partial k} \right) - (\mathbf{t} \cdot \mathbf{m}) \left(\frac{1}{T^2 M} \frac{\partial T}{\partial k} + \frac{1}{TM^2} \frac{\partial M}{\partial k} \right) \\ &= \left(\frac{\mathbf{t} \cdot \mathbf{v} + \mathbf{m} \cdot \mathbf{l}}{TM} \right) - \frac{\mathbf{t} \cdot \mathbf{m}}{TM} \left(\frac{\mathbf{t} \cdot \mathbf{l}}{T^2} + \frac{\mathbf{m} \cdot \mathbf{v}}{M^2} \right) \\ (A1) \quad &= \left(\left(\frac{V}{M} \right) \cos_{tv} + \left(\frac{L}{T} \right) \cos_{ml} \right) - \cos\theta \left(\left(\frac{L}{T} \right) \cos_{tl} + \left(\frac{V}{M} \right) \cos_{mv} \right). \end{aligned}$$

This result holds generally. Now consider neutral learning, $l_i = l$, $v_i = v$. In that case the learning vectors consist of constants with lengths $L = \sqrt{n}l$ and $V = \sqrt{n}v$, and the terms in (A1) simplify. For example:

$$\cos_{tv} = \frac{\mathbf{t} \cdot \mathbf{v}}{TV} = \frac{ntv}{T\sqrt{n}v} = \sqrt{n} \frac{t}{T},$$

and similarly for the other terms. Without loss of generality, assume that the firm rescales P , multiplying it by a constant so that the $\mathbf{m}$ vector has the same length as $\mathbf{t}$, $M = T$. Any scaling can be reversed for compensation purposes by rescaling the incentive intensity b . After some algebra, (A1) simplifies to:

$$(A2) \quad \frac{\partial \cos\theta}{\partial k} = \left(\frac{n}{T^2} \right) [(tv + ml) - \cos\theta(tl + mv)].$$

This reveals condition under which increased learning makes the measure more or less distorted. The fact that $\cos\theta < 1$ means that this expression will tend to be positive; ceteris paribus an increase in the rate of learning reduces distortion. In the limit as $\cos\theta \rightarrow 0$ this is guaranteed. In the other extreme of very low distortion this is not guaranteed, which should not be surprising if P is already closely aligned with Q . As $\cos\theta \rightarrow 1$ the necessary condition approaches $v(t - m) > l(t - m)$. Since $v, t, l, m > 0$, this holds if $t > m$ and $v > l$, or with both reversed. The result is intuitive. If the measure gives more weight to learning than does the production function, a rise in the rate of learning this will increase distortion unless it is counterbalanced by the production function having a larger overall marginal product (and vice versa).