According to psychologists and neuroscientists, a key source of intrinsic motivation is learning. An economic model of this is presented, exploring how job design might drive learning and motivation. 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. A new multitask motivation problem arises 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. Interactions between learning, performance evaluation and incentives are then analyzed. A higher rate of learning tends to reduce performance measure distortion, especially for a significantly distorted measure, though the opposite may also occur. It also tends to reduce potential for classical manipulation of the measure. However, a new form of manipulation may arise if the employee learns not just how to improve output, but also how to better manipulate the evaluation. That is especially likely if job design is strongly imbalanced towards a few key tasks, learning varies significantly across tasks, or the effects of learning on the measure and output differ significantly. The optimal incentive rebalances motivation from learning and towards output, but this is not “crowding out.” The incentive increases total surplus if the measure is not manipulable, but may not do so in the presence of manipulation. Because learning’s effects on performance evaluation effectiveness are ambiguous, the incentive intensity might rise or fall with the rate of learning. Moreover, it might be larger or smaller (or even zero) when the employee is granted autonomy, compared to optimal incentives without autonomy.

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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 economists 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. Incentives serve to rebalance motivation away from the employee’s personal interest in learning, towards firm objectives. They also reinforce the benefits of granting autonomy, if the performance measure is not manipulable.

The model reveals 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 in the traditional sense of that term. However, it may create a new form of manipulation via counter-productive learning, in which the employee learns not just how to improve output, but also how to better manipulate the evaluation. 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 how job design may foster learning, which might then drive intrinsic motivation. 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 em-
phasized the roles of decentralization and incentive pay to use employee knowledge more effectively, but
they have 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 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). Many examples have been
considered, including pro-social behavior, enjoying the activity itself, and deriving a sense of meaning from
the 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). 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 employ-
ment settings. For a history of this topic in economics, see Ramiuc (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.

Learning also appears to be an important source of intrinsic motivation at work. For example, Heath (1999) and Kreps (2018) present data on the relative importance of different sources of motivation in the workplace. Both find that learning, growing, and skill development are ranked highest.

While there are several ways in which scholars in social psychology and organizational behavior think about intrinsic motivation, one particularly influential approach is the Job Characteristics Model (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). Hackman and Lawler state that their model is “designed to implement the idea that learning – and intrinsic motivation – can be stimulated by appropriate job design.” The idea is that intrinsic motivation can be generated by putting the employee into a challenging situation in which thinking and learning is require in order to resolve issues that
are not understood, to acquire new skills, and to develop solutions to problems. This is quite consistent with the evidence from neuroscience described above.¹

The Job Characteristics Model 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 feel 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.”

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, work 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 been considered in economics. However, several of the job characteristics listed above are closely related to topics that economists study: multitasking, discretion (decentralization), and performance evaluation, which is a form of feedback. Those are central elements of the model presented below.²

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 the model.
2. Basic Model

This section introduces the basic model. Production and performance evaluation are based on Holmstrom and Milgrom’s multitask incentive model (1991), as adapted by Feltham and Xie (1994). That is augmented with Lindbeck and Snower’s (2000) idea of intertask learning. Along similar lines, Magee (2005) presents an economic model of creativity based on the notion of “analogical transfer” from psychology, in which information and experiences may be used in searching for solutions to different problems. Multitasking would be an obvious way to operationalize this to foster on the job learning. Psychologists also emphasize the role of multitasking for creativity and learning (Hackman & Lawler 1971; Kapadia & Melwani 2021).

The model adds several elements to employee utility to model intrinsic motivation from learning on the job. “Learning” should be interpreted broadly, and not limited to acquisition of human capital. The term is intended to capture various types of knowledge and information which an employee might create or observe while performing the job. One type might be acquisition of skills that apply to multiple tasks. An important special case 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 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 by $i$, with production function $Q$:

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

This production function appears to be additive. However, we assume below that learning arises from performing other tasks. That generates interdependencies between tasks. 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 $q = \Sigma q_i / n \geq 0$. The second is *intertask learning*, $l_i$. By working on one task, the employee learns and improves productivity on other tasks. The overall rate of learning is $k$. This is a simple way to parameterize environmental factors (e.g., the degree of uncertainty or change; the employee’s skills or cognitive ability) that affect opportunities to learn and improve operations. The task-specific component is $l_i \geq 0$, with average $l = \Sigma l_i / n$. Total learning is $L = \Sigma k l_i e_i$.

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. Our approach is inspired by Lindbeck and Snower’s (2000) model of intertask learning; also see Gibbs, Levenson & Zoghi (2010). Learning should depend on how many and which tasks are bundled together. 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, $l_i = l_i(q_{j \neq i})$, with greater learning from more important tasks. That said, most results below follow for any vector $l_i$. 
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 biased.

**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 \( L = nk(n-1)q \sum e_i \).

**Biased:** 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 \( L = k \sum (nq - q_i) e_i \). 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. Biased learning is more realistic, but neutral is easier to work with and might suffice for some questions.

**Utility**

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

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

The employee has utility from income, disutility from income risk with coefficient of absolute risk aversion \( r \), and marginal disutility of effort \( C \). Effort on all tasks affects disutility symmetrically. This abstracts from intrinsic motivation driven by preference for some 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 \( e \geq 0 \). 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, because both seem plausible and interesting. 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. 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 $\lambda$. These ideas are consistent with Smith’s (1776) observation that specialized, repetitive jobs may be boring and demotivating, the central role of Skill Variety in the Job Characteristics Model, and neuroscience research on causes of intrinsic motivation. The psychological concept of Growth Need Strength is captured by $\lambda$ and $\partial C / \partial k$, as each measures an aspect of the degree of intrinsic motivation from learning.

**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: $Q + \lambda L - \frac{1}{2} \sigma_{\text{pay}}^2 - \frac{1}{2} C \sum (e_i - e)^2$.

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:

$$\max_{e_i} Q + \lambda L - \frac{1}{2} \sigma_{\text{pay}}^2 - \frac{1}{2} C \sum (e_i - e)^2$$

$$\Rightarrow e^* = e + \frac{q_i + (1 + \lambda)kl_i}{C(k)}.$$

The marginal benefits from extra effort include productivity on that task, learning spillovers 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 ($\lambda, C(k)$). A reduction in the onerous of work due to intrinsic motivation has greater value in jobs with higher direct 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:

$$\max_{e_t} \lambda \sum kl_t e_t + S - \frac{1}{2} C \sum (e_t - \bar{e})^2$$

(2)

$$\Rightarrow e_t^* = \bar{e} + \frac{\lambda kl_t}{C(k)}$$

This provides several interesting insights. First, comparing (2) with (1), $\bar{e} < e_t^* < e_t^s$. This follows because $q_i + kl_i = t_i \geq 0$ or the firm would not assign the task. The employee provides efforts without an incentive, but these 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 biased ($l_i$ 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 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, biased learning seems more realistic than neutral, in which case this multitask issue will be present. Thus intrinsic motivation from learning is not necessarily an unmitigated good, as it may generate a conflict of interest between the employee and the firm. Clearly incentive pay might play a role, as will be discussed below.

Multitasking

Multitasking might affect the disutility of effort. 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, which would need to be balanced against learning benefits. That idea could be modelled by
allowing $C$ to be a function of $n$, $C = C(k, n)$. For convenience, treat the number of tasks as continuous, though it is an integer. The effect of $n$ on effort is ambiguous:

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

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.\(^3\) 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 $\partial C/\partial n > 0$. While these effects are interesting and of empirical relevance, we put the issue aside to focus on intrinsic motivation.

**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 and of 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, or to impose their preferences on subordinates (Prendergast & Topel 1996; Perri 2021). However, we follow an approach that is common in the economics literature, treating autonomy as decentralization rather than an additional component of the utility function.

Use of autonomy (decentralization) if the employee possesses “specific knowledge” (knowledge that is costly to communicate to a centralized decision maker) is an important theme in the economics

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\(^3\) Multitasking would reduce coordination costs from specialized work. That, and benefits from intertask learning, are two additional considerations that could be added to Becker and Murphy’s (1992) analysis of specialization and the division of labor.
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 (Lazear & Gibbs 2015). Learning adds an interesting dimension to this idea. Granting autonomy allows the employee to diagnose the work, generate new ideas, and experiment to improve methods in order to create new knowledge.

To consider this issue, assume that the rate of learning is stochastic, \( E\tilde{k} = \tilde{k} \). Further assume that \( E\tilde{t}_i \geq 0 \). 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 is 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 in income and effort.\(^5\)

The firm and employee first negotiate terms of the job (possibly including incentive pay, which is added below). Salary \( S \) may differ between the cases of withholding or granting autonomy. However, it has no effect on decisions 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., \( \tilde{t}, \tilde{C} \)):

\[
\text{Expected total surplus} = E(\text{Output}) + E(\text{Utility})
\]

\[
= E \left\{ \sum \tilde{t}_i e^*_i + \lambda \tilde{k} \sum l_i e^*_i - \frac{1}{2} C(\tilde{k}) \sum (e^*_i - \bar{e})^2 \right\}.
\]

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

\(^5\) Despite this assumption, 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.
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 $\bar{k}$ and $C(\bar{k})$. Denoting $\bar{C} = C(\bar{k})$,

$$\max_{e_i} E \left\{ \sum \lambda \bar{k} l_i e_i + S - \gamma C(\bar{k}) \sum (e_i - \bar{e})^2 \right\}$$

(4)

$$\Rightarrow e_i^N = e + \frac{\lambda \bar{k} l_i}{C}.$$

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, with no incentive, 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:

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

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

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

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

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.

**Feedback**

Hackman and Lawler argue that *Feedback* complements autonomy. They conceive of feedback as arising from doing the work itself (e.g., employees observe how satisfied customers are with their service). However, any source of information on the effects of the employee’s actions should improve learning. When firms implement job designs using these techniques, employees are often expected to collect and evaluate their own data, and may be trained in problem-solving skills (Wruck & Jensen 1994). 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. An additional form of feedback is performance evaluation, which may be used for incentives. That is our next topic.

### 4. Extrinsic and Intrinsic Motivation

Incentives might mitigate multitask incentive problems, including those arising from biased learning. They might also reinforce the benefits of autonomy. At the same time, learning might affect performance evaluation and thus the effectiveness of incentives. These issues are explored in this section.
Performance Measurement

The firm offers a linear bonus with incentive intensity $b$. Output is assumed to be non-contractible, so the bonus is based on performance measure $P$ that proxies for $Q$:

$$P = \sum m_i e_i + \bar{\epsilon} = \sum_{i=1}^{n} (p_i + kv_i)e_i + \bar{\epsilon}.$$  

Measurement error $\bar{\epsilon}$ has variance $\sigma^2$; therefore, $\sigma^2_{P\bar{\epsilon}} = b^2 \sigma^2$. The marginal effect of effort $e_i$ on the evaluation is $p_i$. As with production, we would expect intertask learning about how to improve measured performance: $v_i = v_i(p_j \neq i)$. Ideally, for an effective measure $v_i$ should be as aligned with $l_i$ across tasks as possible. However, most results below follow for any vector $v$. $p_i, v_i$ and $m_i$ may be negative, though for a sensible performance measure their average values across all tasks $(v, p, m)$ should be positive.

The literature on performance measurement highlights two key properties: the extent to which the measure distorts multitask incentives, and the potential for manipulation. Learning affects both.6

Distortion

Distortion of the performance measure arises 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 between the vectors $t_i$ and $m_i$ of marginal effects of effort on output and the performance measure (Baker 2002):

$$\cos_{tm} = \frac{\sum t_i m_i}{TM}.$$  

$T$ 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 $Q$. The lengths of $P$ and $Q$ change with a change in $k$, usually by different magnitudes. Such rescalings are innocuous, as they would be reversed for compensation purposes by the incentive intensity $b$. If $P = Q$, $\cos_{tm} = 1$. The lower is $\cos_{tm}$, the more distorted is the measure.

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6 A third important property of performance measures is noise, $\sigma^2$, which is assumed 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 may have developed more accurate methods of measuring performance, and vice versa.
Manipulation

Manipulation arises if the employee can take actions that improve measured performance, but do not improve (and may harm) firm value. Therefore, a task is manipulable if $m_i < 0$. The usual sense for this is when $p_i < -kv_i < 0$. In this case the employee can improve measured performance by reducing effort on this task, despite learning spillovers to measured performance on other tasks. For example, an accountant might manipulate recognition of revenue. By doing so he or she may learn how to better measure components of revenue, improving performance on some tasks, but at the expense of overstating measured earnings.

If $v_i < 0$, we have counter-productive learning. By increasing effort on this task, the employee learns how to manipulate evaluation of other tasks. Significant counter-productive learning can cause manipulation even if $p_i > 0$, if $kv_i < -p_i$.

Which jobs are more likely to be manipulable? Those which are more narrowly focused, in two senses. First, fewer tasks makes manipulation more plausible, since it is more likely that negative effects of one task overcome positive effects on fewer other tasks. For example, with biased learning $v_i = np - p_i$. Lower $n$ makes this more likely to be negative, all else equal. Second, a key task that dominates other aspects of the job may be more subject to manipulation. With intertask learning about performance measurement ($v_j$ depends on $p_{i \neq j}$), $p_i < -kv_i < 0$ is more likely if task $i$ is relatively important compared to other tasks. These ideas are consistent with the view that broader performance measures (covering more underlying components) are more difficult to manipulate (Lazear and Gibbs 2015, ch. 9).

Effects of Learning on Performance Measurement

Learning changes performance measurement in complex ways. Consider first its effect on distortion. It is shown in Appendix B that:

$$\frac{\partial \cos_{tm}}{\partial k} = \left( \frac{v}{m} \cos_{tv} + \left( \frac{l}{l} \cos_{ml} \right) \right) - \cos_{tm} \left( \left( \frac{l}{l} \cos_{tl} + \left( \frac{v}{m} \cos_{mv} \right) \right) \right),$$

where $\cos_{xy}$ measures the angle between output, measured performance, and the components of each. Intuition might suggest that as the rate of learning rises, the measure becomes better aligned with output, since it affects both. However, that is not guaranteed, because it might not affect them in the same way. Moreover,
what matters is how learning effects across tasks relates to total measured performance and total output, both of which include non-learning effects. Conceivably (though perhaps not realistically in real world practice), performance measure learning effects \( v_i \) across tasks might align weakly with productive learning \( l_i \), but strongly with direct marginal products \( q_i \). Thus greater learning may increase or decrease distortion. Though it is difficult to generalize, some inferences are possible. Appendix B provides details.

First, if the measure is significantly distorted, an increase in \( k \) is more likely to reduce distortion, and vice versa. Learning tends to moderate extreme degrees of distortion in performance measures.

Second, even with neutral learning, a rise in \( k \) might increase distortion. If the measure weights learning more than production does (\( v > l \)), greater learning increases distortion unless it is counterbalanced by higher average marginal product of production compared to the measure (\( t < m \)), and vice versa.

Third, if learning is biased but in the same way for the measure and output (\( v_i = \alpha l_i \), where \( \alpha \) is constant), a similar result holds, except that the counterbalancing effect is relative alignment of learning \( l_i \) with total output \( t_i \) or total performance \( m_i \).

Finally, if learning is biased in different ways for the measure and output, a higher rate of learning is more likely to increase distortion, since it will magnify that difference.

What is the effect of learning on manipulation? Recall that a task is manipulable if \( m_i = p_i + kv_i < 0 \). An increased rate of learning reduces the potential for classical manipulation \( (p_i < -kv_i < 0) \), by increasing positive spillovers to other tasks. By contrast, increased learning makes manipulation due to counter-productive learning \( (v_i < 0) \) more likely, as the employee learns how to cheat more effectively. Note that counter-productive learning is also likely to worsen distortion, as the measure diverges more from actual performance. It has been observed that performance measures may degrade in usefulness over time (Courty & Marschke 2008). Learning provides one potential explanation, since it may worsen distortion and the employee may gradually learn how to better manipulate the measure.\(^7\) For this reason, when designing a job to foster learning, a firm must consider the potential risk that the employee learns how to better game evaluation of performance.

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\(^7\) Another explanation is that the environment changes, so the performance measure should evolve.
Optimal Incentive

For given $b$, the employee chooses efforts to maximize expected utility:

$$\max_{e_i} \lambda L + bP - \frac{1}{2} r b^2 \sigma^2 - \frac{1}{2} \sum (e_i - \bar{e})^2$$

(6)

$$\Rightarrow e_i^* = \bar{e} + \frac{\lambda k l_i + b m_i}{C(k)}.$$

For non-manipulable tasks ($m_i > 0$), effort will be larger than if there is only intrinsic motivation, and will increase if the incentive intensity rises:

(7)

$$\frac{\partial e_i^*}{\partial b} = \frac{m_i}{C}.$$

Both statements are reversed for manipulable tasks.

The firm sets the incentive intensity to maximize total surplus, subject to (6). Doing so and substituting in (6) and (7) yields:

$$\max_b Q + \lambda L - \frac{1}{2} r b^2 \sigma^2 - \frac{1}{2} \sum (e_i - \bar{e})^2$$

$$\Rightarrow \sum t_i \frac{\partial e_i^*}{\partial b} + \lambda \sum k l_i \frac{\partial e_i^*}{\partial b} - r b \sigma^2 - C \sum (e_i - \bar{e}) \frac{\partial e_i^*}{\partial b} = 0$$

$$\Rightarrow \frac{1}{C} \sum t_i m_i + \frac{\lambda}{C} \sum k l_i m_i - r b \sigma^2 - \frac{1}{C} \sum (\lambda k l_i + b m_i) m_i = 0$$

(8)

$$\Rightarrow b^* = \frac{\sum t_i m_i}{\sum m_i^2 + r \sigma^2 C(k)} = \frac{T M c o s t_m}{M^2 + r \sigma^2 C(k)}.$$

Expression (8) is a familiar term in the literature. It exhibits a key purpose of incentive pay in this model: rebalancing distorted incentives. The new element is that learning may also affect distortion and the need for rebalancing. Incentives are rebalanced 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 $t_i$.

A manipulable task reduces the optimal incentive. In (8) manipulation would be reflected by one or more $m_i < 0$, reducing $b^*$ ceteris paribus. It might also be reflected as an increase in $M^2$, 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, increasing the length of $M$. Finally, manipulation might 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 ($\lambda > 0$). That generates personal utility, while the incentive is used to motivate 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 effort levels, 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, but only two always work in that direction. 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.

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. 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? If so, is the optimal incentive larger or smaller with autonomy?

The optimal incentive 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 with autonomy, since the problem would otherwise be intractable with stochastic $\tilde{k}$). With autonomy, $e^a_t$ is as in (6). With no autonomy, $e^N_t$ is similar to (4), with a new term reflecting the incentive:
The method that was used to derive (8) yields the optimal incentive intensity with or without autonomy. First consider the incentive with no autonomy:

\[ b^N = \frac{\sum \tilde{t}_i \bar{m}_i}{\sum \bar{m}_i^2} = \frac{\tau}{M} \cos \bar{m}. \]

In effect, the performance measure is \( \bar{P} = \sum \bar{m}_i e_i \), and the firm wants to motivate the employee to increase expected output \( \bar{Q} = \sum \tilde{t}_i e_i \). Distortion of this measure is \( \cos \bar{m} \), which \( b^N \) rescales to the extent that \( M \neq \bar{T} \).

Use of an incentive will increase expected total surplus in the case with no autonomy, because it better aligns employee and firm interests when neither has private information. This can be shown by a straightforward extension of the proof that expected total surplus rises with autonomy in the no incentive case, including the effect of the incentive on effort.

With autonomy, the optimal incentive is:

\[ b^A = \frac{E \sum t_i m_i}{E \sum m_i^2} = \frac{\sum \tilde{t}_i \bar{m}_i + \sum \text{cov}_{t_i,m_i}}{\sum \bar{m}_i^2 + \sum \sigma_{m_i}^2} = \frac{\sum \tilde{t}_i \bar{m}_i + \sigma_k^2 \sum l_i \sigma_l}{\sum \bar{m}_i^2 + \sigma_k^2 \sum v_i^2}. \]

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 \( m_i \) well with \( t_i \), 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 performance measure vector. Since \( t_i \) and \( m_i \) vary with \( l_i \) and \( v_i \) as the rate of learning varies, \( b^A \) will be larger to the extent that \( l_i \) and \( v_i \) are well aligned, and vice versa. This is seen in the last terms in the numerator and denominator in (9).

If there is no manipulation (\( m_i > 0 \) and \( v_i > 0 \)), using the same methods as above, it is straightforward to show that an optimal incentive increases expected total surplus with autonomy. However, if the measure

\[ e_i^N = e + \frac{\lambda_i k}{C} + \frac{b \bar{m}_i}{C}. \]
is manipulable this result is not guaranteed, since the employee might exploit this, causing a net loss of profit – output minus pay – to the firm. For this reason, and unlike in the prior literature, the optimal incentive is not necessarily larger if the employee is granted autonomy. Moreover, it may not be increasing in the extent of knowledge or environmental uncertainty which the employee gains from autonomy \( \sigma_k^2 \). Furthermore, derivations of optimal incentives assume interior solutions, but those are not guaranteed, in which case the optimal incentive with autonomy might be zero. This depends on how performance measure quality varies with learning. If learning improves the evaluation, incentives should rise with autonomy. If it does not, autonomy generates a new 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; Frey & Jegen 2001). This model provides little support for that view, and is more consistent with Eisenberger and Cameron’s (1996) conclusion that the problem arises under narrow and easily avoided conditions, and that rewards can motivate creativity. In this model, incentives sometimes 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 learning. 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, empirically 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 if it is 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 counter-productive, 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. To the extent that steps in the process can be bundled into relatively separable modules (with significantly lower task coordination costs within 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.

A multiperiod approach to learning would be more realistic. This would facilitate consideration of accumulation of knowledge, as well as evolution of techniques, job design, and performance measurement. The latter could allow analysis of Feedback as coaching and 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 engine factory). Each team member specializes in some set of tasks, 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 (Ortega 2006) and reducing coordination costs (Becker and Murphy 1992). 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 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 recruitment, job design and performance evaluation should be more important when the firm has more to learn: the product or process is complex, the environment is changing, or it is unpredictable. And of course firms may use both methods for different employees.

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. 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), suggesting increased intrinsic motivation. Caroli and van Reenen interpreted their findings as evidence for skill-biased organizational
change. It seems reasonable to also interpret these findings as evidence for intrinsic motivation-biased organizational change. 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.

The model revealed complex interactions between learning and performance evaluation. The approach to evaluation modeled in this paper 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 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. Many employee insights will be complex and intangible, evaluation of which may require judgment. The job will evolve, so the evaluation should also evolve, and effective relational contracting for subjective evaluation will make that easier (Courty and Marschke 2003). 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 endogenous, and 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 cause, and this is well supported by neuroscience research. This paper has attempted to bring these literatures together. 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 complementary tasks, 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 tasks 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 employee utility. Employees may value learning intrinsically. 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.
Learning that is biased across tasks generates a new multitask motivation 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. Incentive pay serves to balance intrinsic motivation with firm objectives. If the employee cannot manipulate the measure, it also complements use of autonomy to foster learning. A number of interesting complications arise when learning affects the employee’s evaluation. It might cause greater distortion or manipulation of the measure. If the measure is already well aligned with output, learning may worsen distortion, and vice versa. Learning that is counter-productive for some task increases the potential for the employee to manipulate the measure. In that case optimal incentives might be lower or even zero with autonomy. 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 more progress in understanding how learning affects performance measurement. Most importantly, study of these topics seem incomplete without consideration of intrinsic motivation.

All of these issues are ripe for empirical research. Also of interest would be measurement of 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, how do they vary across occupations, types of jobs, and extent of cognitive tasks? 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; Arellano-Bover & Saltiel 2021; Gill & Prowse 2021). It would be of similar interest to understand how supply and demand for employees with preferences for learning plays out in the labor market.
References


Appendix A: Representation of Job Characteristics Model

Source: Hackman & Oldham (1976), Figure 1.
Appendix B: Effect of Learning on Performance Measure Distortion

Vectors are in **bold**. Use inner product notation, e.g., \( \textbf{t} \cdot \textbf{m} = \Sigma t_i m_i \). Vector lengths are capitals, e.g., 
\[ T = (\textbf{t} \cdot \textbf{t})^{\frac{1}{2}}. \]

\[
\frac{\partial T}{\partial k} = \frac{1}{2} (\textbf{t} \cdot \textbf{t})^{-\frac{1}{2}} (2 \textbf{t} \cdot \textbf{l}) = \frac{\textbf{t} \cdot \textbf{l}}{T},
\]

and similarly for \( M \). Distortion is \( \cos_m = \frac{\textbf{t} \cdot \textbf{m}}{TM} \leq 1 \).

\[
\frac{\partial \cos_{tm}}{\partial k} = \frac{1}{TM} \left( \frac{\partial \textbf{t} \cdot \textbf{m}}{\partial k} - (\textbf{t} \cdot \textbf{m}) \left( \frac{1}{T^2 M} \frac{\partial T}{\partial k} + \frac{1}{TM^2} \frac{\partial M}{\partial k} \right) \right)
\]

(A1)

\[
= \left( \frac{\textbf{t} \cdot \textbf{v} + \textbf{m} \cdot \textbf{l}}{TM} - \frac{\textbf{t} \cdot \textbf{m}}{TM} \left( \frac{\textbf{t} \cdot \textbf{l}}{T^2} + \frac{\textbf{m} \cdot \textbf{v}}{M^2} \right) \right)
\]

(A2)

The fact that \( \cos_m < 1 \) imparts a tendency for this expression to be positive, especially for \( \cos_m \) close to 0. This suggests that if a measure is very distorted, a higher rate of learning will tend to make the measure even less distorted, while the opposite is true if the measure was already well aligned with output. That result has intuitive appeal. It is not guaranteed, though, since learning affects distortion via how its effects on output and the measure align with the measure and total output.

Further insights can be provided for specific and empirically relevant cases: where learning is neutral, or biased but in the same way for output and the measure. In what follows, without loss of generality assume that the firm rescales \( P \), multiplying it by a constant so that \( \textbf{m} \) has the same length as \( \textbf{t} \), \( M = T \). Any scaling would be reversed for compensation purposes by rescaling the incentive intensity \( b \).

First consider neutral learning, \( l_i = l, v_i = v \). The learning vectors consist of constants with lengths 
\[ L = \sqrt{n}l \text{ and } V = \sqrt{n}v, \] and the terms in (A1) simplify. For example:

\[
\cos_{tv} = \frac{\textbf{t} \cdot \textbf{v}}{TV} = \frac{ntv}{T \sqrt{n}v} = \frac{t}{\sqrt{V}},
\]

and similarly for the other terms. After some algebra, (A1) simplifies to:

\[
\frac{\partial \cos_{tm}}{\partial k} = \left( \frac{n}{T^2} \right) [(tv + ml) - \cos_{tm}(tl + mv)].
\]
When is this expression positive, so that greater learning reduces performance measure distortion? As $\cos_{tm} \to 0$ (high distortion) the expression becomes positive. As $\cos_{tm} \to 1$ (low distortion) the necessary condition approaches $(t - m)(v - l) > 0$. Since $v, t, l, m > 0$, this holds if $t > m$ and $v > l$, or with both reversed. The result is intuitive. If a measure has low distortion and gives more weight to learning than does the production function, greater learning increases distortion unless that is counterbalanced by production having a larger overall marginal product than the measure (and vice versa).

A similar result holds when learning is biased, but in the same way for the measure as for output, so that $v_i = aL$. Then $V = aL, \cos_{tv} = \cos_{dv}, \cos_{vl} = 1$, and (A2) simplifies to:

$$\frac{\partial \cos_{tm}}{\partial k} = \left(\frac{L}{T}\right)\left(\left(\alpha \cdot \cos_{tl} + \cos_{ml}\right) - \cos_{tm}\left(\cos_{tl} + \alpha \cdot \cos_{ml}\right)\right)$$

$$= \left(\frac{L}{T}\right)\left(\cos_{tl}(\alpha - \cos_{tm}) + \cos_{ml}(1 - \alpha \cdot \cos_{tm})\right).$$

Once again, as $\cos_{tm} \to 0$ this expression becomes positive, reinforcing the conclusion that if a measure is highly distorted, greater learning mitigates this problem. As $\cos_{tm} \to 1$, this expression will still be positive if $(\cos_{tl} - \cos_{ml})(\alpha - 1) > 0$. Intuitively, if a measure with low distortion gives more weight to learning than does production, greater learning increases distortion unless learning covaries significantly more with total output than with the measure. Of course, that (and similar patterns of biased learning for the measure and output) will often be plausible, since the measure is chosen to mimic production. This further reinforces the notion that an increase in the rate of learning will tend to reduce performance measure distortion.

Finally, all else equal, if learning is biased, the less similar are intertask learning for the measure and output ($\cos_{vl} < 1$), the more likely will it be that greater learning worsens distortion, because that would magnify the problem.