According to psychologists and neuroscientists, learning is a key source of intrinsic motivation. A model is developed in which job design drives learning and motivation. Multitasking generates learning: performing one task increases productivity on related tasks. A new multitask alignment problem arises if the rate of learning varies across tasks. The model highlights the importance of effective job design to generate valuable intrinsic motivation. If the job promotes learning closely aligned to output, intrinsic motivation and autonomy are complements, particularly in environments with greater uncertainty. These effects are stronger if the employee is more intrinsically motivated, skilled, or creative. Interactions between learning, evaluation and incentives are then analyzed. For reasonable measures, greater learning tends to make measures less distorted and manipulable, and reinforces intrinsic motivation, rebalancing motivation towards output relative to learning. However, learning may make performance measurement worse. A new form of manipulation arises if the employee learns how to better manipulate the measure. That is more likely if job design is narrowly focused, learning varies significantly across tasks, or effects of learning on the measure and output differ significantly. In that case, incentives might not be optimal, especially if the employee is given autonomy, and the firm might rely solely on intrinsic motivation.

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1. Introduction

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

The form of intrinsic motivation analyzed here is 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 decision making, performance evaluation, and incentives. Moreover, effective use of knowledge, innovation and continuous improvement have been themes in economics for many years. Designing the job to tap the motivation to learn can be an important way to pursue these objectives.

To model the role of learning, two 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. The second addition builds on this to model intrinsic motivation, by assuming that the employee personally values learning. The results point to the importance of effective job design and performance evaluation. If the firm designs the job appropriately, it can motivate
greater intrinsic motivation that is better aligned with firm objectives, providing an effective way to moti-
vate organizational learning and adaptation. Similarly, if effective performance measures are available, in-
centives can then reinforce intrinsically motivated learning. However, learning may also undermine perfor-
manee evaluation, especially in narrow, unbalanced jobs with learning effects that vary significantly across
tasks. When that is the case, the firm might be better off relying solely on intrinsic motivation. Thus, many
aspects of organizational design that have been studied theoretically and empirically by economists may
not require incentive compensation.

On-the-job learning motivates greater effort than would otherwise be provided, absent incentive
pay, and partially aligns interests between the firm and the employee. However, if the rate of learning varies
across tasks, a new multitask motivation problem emerges, as motivation is biased towards learning-inten-
sive tasks, while the firm cares about output.

Even though intrinsic motivation is not perfectly aligned with firm interests, it increases total sur-
plus because the employee’s interest in learning also benefits the firm. A similar result arises when we allow
for autonomy (decentralization). Autonomy reinforces learning, allowing the employee to become better
informed, test ideas, and implement improvements. Granting autonomy increases surplus when there is no
incentive pay, and even more so, the greater the employee’s intrinsic motivation.

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 measure more difficult to manipulate in the traditional sense of that
term. However, a new form of manipulation may arise via counter-productive learning, in which the em-
ployee learns not just how to improve output, but also 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
the measure is not very manipulable, which in turn depends on job design. If potential for manipulation is significant, the firm might use autonomy or incentives but not both.

The model provides a framework for analyzing how job design can foster learning that then drives 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 that appears to be important in practice. Economists have emphasized the roles of decentralization and incentive pay to use employee knowledge more effectively, but have less often considered how to design organizational policies to create knowledge. Intrinsic motivation may be a key method by which firms can do so.

a. 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. For a history of this topic in economics, see Ramaniuc (2017). 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 because firm policies can be used to increase such motivation.

A small number of papers model intrinsic motivation of employees. Murdock (2002) analyzes a setting in which employees derive utility from a non-financial aspect of output (e.g., a social mission that firm activities might affect). Bénabou and Tirole (2003) provide a model in which incentives may affect motivation if they change an employee’s perception of his or her abilities in performing the task. Prendergast models intrinsic motivation caused by preferences over different aspects of performance, or for performing some tasks compared to others (2007, 2008). Cassar and Meier (2018) survey 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.
Beckmann and Kräkel (2022) study how empowerment may generate pride and a sense of ownership over the work. Kreps (forthcoming) discusses several sources of intrinsic motivation and provides formal analysis of the desire to take actions that benefit another person, similar to Becker’s theory of altruism (1974). None of these papers considers the role of employee learning. Kreps (1997) advises economists that to model intrinsic motivation, “excursions into cognitive and social psychology are warranted.” That is done in this paper.

Intrinsic motivation has received far more attention in psychology. 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 situations that are not fully understood: “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 multitasking produces anxiety.

Learning also appears to be an important source of intrinsic motivation at work, and one that employees value. 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, consistent with the emphasis on learning in psychology. Helliwell and Huang (2010) estimate compensating differentials for non-financial job characteristics. “Trust in management” is ranked highest, but “Job requires skill” and “Job has a variety of tasks” are next. They find that the percentage income equivalence for a one-third standard deviation increase in these last two characteristics is 18% and 16.6% respectively.
While there are several ways in which scholars in social psychology and organizational behavior think about intrinsic motivation, what is probably the most 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., 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 required 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 model posits five job characteristics and one “moderator” (employee characteristic) that may generate intrinsic motivation:

- **Skill Variety**: degree to which a job requires a variety of different skills, and thus tasks.
- **Task Identity**: degree to which the job involves a “whole” and identifiable piece of work.
- **Task Significance**: degree to which the employee 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.”

Figure 1 shows a graphical representation from Hackman and Oldham (1976); similar figures appear in many organizational behavior textbooks.

*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, involving observation, diagnosis, hypothesis formation, and

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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.
problem solving. An employee with higher Growth Need Strength is more intrinsically motivated by this cognitive challenge. An interpretation of Task Identity will emerge from the model.²

This view accords well with Smith’s observation that specialized, routine jobs do not engage a worker’s mind and may be demotivating (1776; book 5, chapter 1): “The man whose whole life is spent in performing a few simple operations, of which the effects are perhaps always the same, or very nearly the same, has no occasion to exert his understanding or to exercise his invention in finding out expedients for removing difficulties which never occur. He naturally loses, therefore, the habit of such exertion, and generally becomes as stupid and ignorant as it is possible for a human creature to become.”

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 one form of feedback. Those are central elements of the model presented here.

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). In addition, the model adds an element to employee utility to model intrinsic motivation from learning on the job.

² Task Significance accords well with Murdock (2002), in which the employee gains utility from certain aspects of output. It will not play a role here.
“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.

Another 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 are shopping. Such information is valuable for deciding which products to pitch, and for choosing the most effective selling technique for that customer. This is similar to economic models of discretion (Prendergast 2002; Ortega 2009; DeVaro & Kurtulus 2010). We enrich that approach by considering how job design and intrinsic motivation help the employee acquire such information.

A final form of learning is innovation or continuous improvement. These may arise if performing a more complex job stimulates creativity, making the employee think more broadly, see connections across different parts of the business, gain new perspectives, and abstract lessons to apply elsewhere (Coelho and Augusto 2010).

**a. 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*, $k_{li}$. 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 factors (e.g., degree of uncertainty or change; employee characteristics: skills, cognitive ability, or creativity) that affect opportunities to learn. The task-specific component is $l_i \geq 0$, with average $l = \Sigma l_i/n$. Total learning is $L = \Sigma k_{li}e_i$.

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

Intertask learning operationalizes the social psychology concept of Skill Variety, which is neuroscience research on causes of intrinsic motivation. 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 $l_i$.

One issue that arises 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. We define two general types of intertask learning – neutral and biased.

**Neutral**: performing each task generates identical productivity improvements for all other tasks, $l_i = l$. Then total learning is $nkl\Sigma e_i$. 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, \( l_i = \tau(n-1)q \). This term includes \( n-1 \) because learning improves performance on all other tasks. Total learning is then \( L = \tau n(n-1)kq \Sigma e_i \).

**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 \( l_i = \Sigma_{j \neq i} q_j = nq - q_i \), and \( L = k \Sigma (nq - q_i) e_i \). The average is the same as in the neutral learning example, \( \Sigma l_i / n = (n-1)q \), but learning varies across tasks. Biased learning is more realistic, but neutral is easier to work with and might suffice for some questions.

**Optimal Job Design**

A few quick remarks about optimal job design may be made. First, tasks with greater intertask learning should be bundled together, raising average \( l \). One likely outcome is 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 Task Identity in the Job Characteristics Model.

Second, in this model adding another task to the job will generally increase learning and output. For example, with neutral learning, \( L = \tau n(n-1)kq \Sigma e_i \). Then \( \partial Q / \partial n = \partial L / \partial n = \tau (2n-1) k q \Sigma e_i > 0 \). This accords well with the emphasis given to multitasking in psychological discussions of learning.

Furthermore, the contribution of learning to total surplus is \((1+\lambda)L\), and \( L \) is a function of \( k \). Therefore, multitasking is more valuable if the worker is more intrinsically motivated, has higher cognitive ability or other skills, or there are greater opportunities for learning (the latter two would increase \( k \)).

However, these benefits of multitasking would be counterbalanced by lower specialization of human capital (not modelled here), and the effects on effort disutility. Hackman and Oldham note that if a job is too complex, it can be stressful; this is why they introduced the concept of GNS. Psychological research confirms this (Di Domenico & Ryan (2017)). Economic 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 a high degree of multitasking. That idea could be modelled by allowing the marginal disutility of effort \( C \) to be a function of \( n \), with \( \partial C / \partial n \geq 0 \). We will see below that optimal effort \( e_i \) on a task is increasing in \( l_i \) and decreasing in \( C \). For convenience, treat the number of tasks as continuous, though it is an integer. Even if \( \partial l_i / \partial n \geq 0 \), the effect of \( n \) on effort is ambiguous:

\[
\frac{\partial e_i^*}{\partial n} = \frac{\partial e_i^*}{\partial l_i} \frac{\partial l_i}{\partial n} + \frac{\partial e_i^*}{\partial C} \frac{\partial C}{\partial n} \geq 0,
\]

since optimal effort falls as \( C \) increases. Adding tasks may increase learning, but at the expense of making the work more onerous.

For the remainder of the paper, the number of tasks is fixed, in order to focus on other issues.

b. Utility

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

\[
Utility = \lambda L + E[Pay] - \frac{1}{2} r \sigma_{pay}^2 - \frac{1}{2} \gamma C \sum e_i^2.
\]

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).

Intrinsic motivation is modeled by assuming that the employee has marginal utility \( \lambda \) from learning. This parameter corresponds to the psychological concept of Growth Need Strength, which will be referred to as GNS or \( \lambda \) below.\(^3\) For example, economists may enjoy new knowledge gained from research or teaching, even if it provides no value to the university.

\(^3\) In earlier drafts, a second type of intrinsic motivation was included by assuming that the marginal disutility of effort was a declining function of the rate of learning, \( C(k) \). The results are essentially the same as here. Details are available on request.
c. Profit & First-Best Effort

The firm is risk neutral and maximizes expected profit $Q - E(Pay)$. Pay includes base salary $S$, and possibly a bonus. Total surplus equals profit plus utility, which nets out pay: $TS = Q + \lambda L - \frac{1}{2} r \sigma_{\text{pay}}^2 - \frac{1}{2} C \sum e_i^2$. Throughout, it is assumed that the employee’s participation constraint is met.

Designing the job to increase learning improves productivity and benefits an employee who is intrinsically motivated to learn. Holding efforts fixed, a higher rate of learning $k$ increases employee utility, firm output, and thus total surplus.

First-best effort on each task maximizes total surplus:

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

(1)

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

The marginal benefits from extra effort include productivity on that task, learning spillovers for other tasks, and the employee’s utility from that learning. These are balanced against the marginal disutility of effort. First-best effort rises with the level of the employee’s intrinsic motivation, and 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:

$$\max_{e_i} \lambda \sum k l_i e_i + S - \frac{1}{2} C \sum e_i^2$$

(2)

$$\Rightarrow e_i^* = \frac{\lambda k l_i}{C}.$$ 

This provides several interesting insights. First, comparing (2) with (1), $e_i^* < e_i^s$. 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, greater intrinsic motivation increases 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. If possible, a firm should recruit those with high GNS $\lambda$ into jobs where learning is important, and vice versa.

Third, efforts rise if the job is designed to improve intertask learning, increasing $l_i$.

Fourth, if learning is biased ($l_i$ varies across tasks), intrinsic motivation creates a new type of multitask motivation problem. The employee allocates effort with a bias (relative to $e_i^2$) towards tasks that provide more learning. This is not caused by an innate preference for some tasks relative to others. 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.

a. 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. This emphasizes the functional role that autonomy plays in fostering learning.

Use of autonomy if 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). Autonomy may also encourage the employee to take initiative in acquiring information (Aghion & Tirole 1997) and help the organization adapt by varying effort across tasks (Dessein & Santos 2006). These ideas are quite relevant in our context, and
learning adds interesting new dimensions. 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, chapter 5). Clearly it is one method of information acquisition, but it goes beyond that. Autonomy allows the employee to create new knowledge by diagnosing the work, generating new ideas, and experimenting to improve methods. This type of continuous improvement is a fundamental method that firms use to adapt. Finally, intrinsic motivation might reinforce all of these, though as we shall see not always.

To consider this issue, assume that the rate of learning is stochastic, \( E\tilde{k} = \bar{k} > 0 \). This implies that \( E\tilde{t}_i \geq 0 \). Denote random variables with tildes and expected values with bars (e.g., \( \bar{t} = t(\bar{k}), \bar{k} = E(\bar{k}) \)). The firm does not observe \( k \). If it centralizes decision making, the employee chooses optimal efforts without observing \( \bar{k} \). If it decentralizes, the employee observes \( \bar{k} \) and then chooses optimal efforts. 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). That is intractable since income risk depends on effort levels and is no longer additive. For this reason, discussions of autonomy (including when incentive pay is added below) assume that the employee is risk neutral in income.

The firm and employee first negotiate terms of the job. Salary \( S \) may differ between the cases of withholding or granting autonomy. However, it has no effect on effort choices, 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 \( k \):

\[
E(\text{total surplus}) = E \left[ \sum \tilde{t}_i e_i + \lambda \bar{k} \sum l_i e_i - \gamma \bar{C} \sum e_i^2 \right].
\]

Without autonomy, effort \( e_N^i \) is chosen to maximize expected utility with stochastic \( \bar{k} \):

\[
\max_{e_i} E \left[ \sum \lambda \bar{k} l_i e_i + S - \gamma \bar{C} \sum e_i^2 \right]
\]

\[
\Rightarrow e_N^i = \frac{\lambda \bar{k} l_i}{C}.
\]
With autonomy, effort is chosen with knowledge of $k$, so $e_i^A = e_i^*$ as in (2). Actual efforts will be above or below efforts with no autonomy, as the employee reacts to variation in the rate of learning $k$.

Notice that $Ee_i^N = Ee_i^A$. Average efforts will be equal, but with autonomy efforts rise and fall depending on the values of $k$ and $l_i$. This result will be useful below, as it implies that any change in expected output with autonomy arises solely from intertask learning:

\[
E(Q^A - Q^N) = \sum t_i [Ee_i^N - Ee_i^A] + \frac{\lambda}{c} \sum l_i^2 [E(k^2) - \bar{k}^2] = \frac{\lambda}{c} L^2 \sigma_k^2 = E(L_A - L^N) \geq 0,
\]

where $L$ is the length of the vector $l_i$.

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. The employee uses knowledge of $k$ to increase utility from learning, but that learning also benefits the firm. The combined benefit to the firm and employee from granting autonomy equals $(1 + \lambda)E(L_A - L^N)$.

However, greater variation in effort under autonomy generates higher expected disutility of effort since $-\frac{1}{2}C \sum e_i^2$ is concave in efforts. Put another way, the employee is effort risk averse at the initial negotiation stage.$^4$ Nevertheless, the employee can choose the same efforts as without autonomy, but does not have to. Therefore, it must be that the employee’s benefits from greater learning outweigh the greater disutility of effort, if autonomy is chosen.

Putting these together, autonomy increases expected total surplus because total output rises, and the employee’s utility ignoring base salary rises. These expected gains will be split at the initial negotiation stage. Whether the base salary is higher or lower with autonomy depends on the bargaining power of the firm and the employee. Since on net other elements of utility rise, it is conceivable that base salary falls when the firm grants the worker autonomy. That would be consistent with the evidence in Stern (2004) that scientists often accept lower paying job offers that involve more scientific research. It would be interesting to obtain more general evidence on this question.

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$^4$ Effort risk aversion is plausible and an interesting topic for empirical research. To my knowledge it has not been studied.
It is not possible to make a general statement about whether the value of autonomy increases with the expected rate of learning \( \bar{k} \). However, the value of autonomy increases with the extent of environmental uncertainty. Consider any mean-preserving spread in the distribution of \( \bar{k} \), including a rise in \( \sigma_k^2 \). There is then greater value to allowing the employee to exploit this variation, and (4) will be larger. This extends Prendergast’s (2002) argument that delegation may be optimal when the work environment is uncertain. He focuses on complementarity between environmental risk, autonomy, and incentives. Our result shows that this also holds if the only motivation is intrinsic, and that the benefits of autonomy rise with the employee’s GNS \( \lambda \). Moreover, the effect of environment uncertainty is not just on information acquisition, but also on knowledge creation. Finally, the benefits of autonomy are also larger if there is higher intertask learning \( L \). Thus, designing jobs to foster learning, autonomy, and hiring more intrinsically motivated employees are complements.

c. Feedback

Hackman and Lawler argue that Feedback complements autonomy.\(^5\) 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 misalignment of interests between the firm and employee arising from intrinsic motivation for biased learning. They might also reinforce the benefits of autonomy. At the same

\(^5\) This suggests that they envisioned autonomy not just as something the employee values in and of itself, but as instrumental for learning, which is the approach taken here.
time, learning might affect performance evaluation and thus the effectiveness of incentives. These issues are explored in this section.

**a. 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 $Q$:

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

Measurement error $\bar{\varepsilon}$ has variance $\sigma_{\bar{\varepsilon}}^2$; therefore, $\sigma_{P_{\text{pay}}}^2 = b^2 \sigma_{\bar{\varepsilon}}^2$. 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: $v_i = v_i(p_j \neq i)$. $p_i$, $v_i$, and $m_i$ may be negative. For a sensible performance measure their average values across all tasks ($v$, $p$, $m$) should be positive, which is assumed. Ideally, the measure should be as aligned with across tasks as possible, with higher levels of $\sum q p_i$ and $\sum l v_i$. Therefore, assume that $\sum l v_i \geq 0$. However, most results below follow for any vector $v$.

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 arises to the extent that marginal effects of efforts 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 $m_i$ (Baker 2002):

$$\cos_{\text{tm}} = \frac{\sum t_i m_i}{T M}.$$  

$T$ 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

---

6 A third important property of performance measures is noise, $\sigma_{\varepsilon}^2$, which is assumed exogenous. In practice, it is likely that noise will be larger in environments in which learning is more extensive, so that $\sigma_{\bar{\varepsilon}}^2$ and $\sigma_{\varepsilon}^2$ are positively correlated across jobs. If the firm already understands the production environment very well, it may have developed more accurate methods of measuring performance, and vice versa.
by different magnitudes. Such rescalings are innocuous, as they would be reversed for compensation purposes by the incentive intensity $b$. If $t_i = m_i \forall i$, $cos_{sm} = 1$. The lower is $cos_{sm}$, the more distorted is the measure. That is caused by less alignment of $p_i$ with $q_i$, and $v_i$ with $l_i$. Assume that $cos_{sm} > 0$. Otherwise, $P$ would be a poor choice of performance measure (though the firm might use $-P$).

**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 $v_i > 0$ and $p_i < -kv_i < 0$. In this case the employee can improve measured performance by *reducing* effort on this task, despite beneficial 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*, a new type of manipulation. 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 $kv_i < -p_i$.

Many results below hold if the performance measure is not too manipulable. There is no manipulability if $p_i, v_i \geq \forall i$. Weaker conditions that emerge below in some cases are that $\sum q_ip_i, \sum q_iv_i, \sum p_il_i$, and $\sum l_iv_i$ are $\geq 0$. These conditions hold if marginal products of effort on components of output and the measure do not reverse each other overall.

Which jobs are more likely to be manipulable? Those which are more narrowly focused, in two senses. First, manipulation is more plausible if the job has fewer tasks, since it is more likely that negative effects of one task overcome positive effects on fewer other tasks. For example, if learning from task $i$ raises measured performance on all other tasks proportionally, $v_i = np - p_i$. 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. The condition that $p_i < -kv_i < 0$ is more likely if task $i$ is relatively important. These ideas are
consistent with the view that broader performance measures (covering more underlying tasks) 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 A that:

\[
\frac{\partial \cos \theta_m}{\partial k} = \left( \frac{v}{M} \cos \theta_M + \left( \frac{t}{T} \cos \theta_T \right) - \cos \theta_M \left( \frac{v}{M} \cos \theta_M + \left( \frac{t}{T} \cos \theta_T \right) \right) \right). 
\]

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. What matters is how learning across tasks relates to total measured performance and total output, both of which include non-learning effects. Conceivably (though perhaps not realistically in practice), performance measure learning effects \( v_i \) 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 A 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 (high or low) degrees of distortion in performance measures. That suggests that for typical measures, greater learning will reduce distortion.

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 may increase 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 \( (v_i = a l_i, \text{ where } a \text{ is constant}) \), a similar result holds, except that the counterbalancing effect is relative alignment of learning \( l_i \) with output \( t_i \) or performance \( m_i \).

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

What is the effect of learning on manipulation? Recall that a task is manipulable if \( m_i = p_i + k v_i < 0 \). An increased rate of learning reduces the potential for classical manipulation \( (v_i > 0 \text{ and } p_i < -k v_i < 0) \),
by increasing positive spillovers to other tasks. By contrast, increased learning makes manipulation due to counter-productive learning ($v_j < 0$) 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 explanation, since it may worsen distortion and the employee may gradually learn how to better manipulate the measure. 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.

b. Optimal Incentive

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

$$\max_{e_i} \lambda L + bP - \frac{1}{2}rb^2\sigma_e^2 - \frac{1}{2}C \sum e_i^2$$

$$\Rightarrow e_i^* = \frac{\lambda kl_i + bm_i}{C}$$

(5)

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:

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

(6)

Both statements are reversed for manipulable tasks. The extent to which effort varies with the incentive is independent of the employee’s GNS $\lambda$.

The firm sets the incentive intensity to maximize total surplus, subject to (5). Doing so and substituting in (5) and (6) yields:

$$\max_b Q + \lambda L - \frac{1}{2}rb^2\sigma_e^2 - \frac{1}{2}C \sum e_i^2$$

$$\Rightarrow \sum \epsilon_i \frac{\partial e_i^*}{\partial b} + \lambda \sum kl_i \frac{\partial e_i^*}{\partial b} - rb\sigma_e^2 - C \sum e_i^* \frac{\partial e_i^*}{\partial b} = 0$$

7 Another explanation is that the environment changes, so the performance measure should evolve.
\[ \Rightarrow \frac{1}{\epsilon} \sum t_i m_i + \frac{\lambda}{\epsilon} \sum k l_i m_i - r b \sigma_e^2 - \frac{1}{\epsilon} \sum (\lambda k l_i + bm_i) m_i = 0 \]

(7) \[ \Rightarrow b^* = \frac{\sum t_i m_i}{\sum m_i^2 + r \sigma_e^2 \epsilon} = \frac{TM \cos tm}{M^2 + r \sigma_e^2 \epsilon} \geq 0. \]

Expression (7) is a familiar term in the literature. It exhibits a key purpose of incentive pay. In this model, incentives rebalance motivation towards direct marginal productivity \( q_i \) relative to learning \( l_i \). That works well to the extent that \( m_i \) is reasonably aligned with \( t_i \).

Any task that is manipulable reduces the optimal incentive. In (7) manipulation would be reflected by one or more \( m_i < 0 \). That will increase \( M \), 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. Manipulation should also reduce \( cos tm \) since some components of \( M \) would be negative.

The optimal incentive is independent of the employee’s GNS \( \lambda \). That generates personal utility, while the incentive is used to motivate additional interest in output.

Appendix B shows that if the performance measure is not very manipulable, expected total output, learning, and the disutility of effort all rise when an incentive is added (with or without autonomy). If effort risk aversion is not too severe, the firm will add the incentive and total surplus will rise. The larger surplus will be split by both sides. The change in base salary will reflect both increased utility from learning and a larger effort risk premium. Note that these statements hold for any level of performance measure distortion, as a key purpose of adding an incentive is to reduce the effects of distortion.

**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, a new issue is that learning may affect distortion and manipulation. It is straightforward to prove that \( b^* \) rises with \( k \) if learning has neutral effects on both output and the measure, and average marginal product and learning effects are the same for both \( (p = q \text{ and } v = l) \). That conclusion is not always true. There are two effects. Greater learning increases marginal products, so there is more value to an incentive. At the same time, it 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 (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? Empirical evidence on these questions is mixed (Prendergast 2002; Ortega 2009; DeVaro & Prasad 2015; Rohlfing-Bastian & Schöttner 2017).

Assume that \( k \) is stochastic. The optimal incentive can be derived with or without autonomy by maximizing expected total surplus subject to the employee’s optimal effort choices (ignoring income risk aversion as previously with autonomy). With autonomy, \( e_i^A \) is as in (5). With no autonomy, \( e_i^N \) is similar to (3), with a new term reflecting the incentive:

\[
e_i^N = \frac{\lambda k_i}{C} + \frac{b m_i}{C}.
\]

The method that was used to derive (7) yields the optimal incentive intensity with or without autonomy. First consider the incentive with no autonomy:

\[
b_N = \frac{\sum e_i m_i}{\sum m_i^2} = \frac{\mu}{\overline{M}} \cos \bar{m}.
\]

In effect, the performance measure is \( \bar{P} = \sum m_i e_i \), and the firm wants to motivate the employee to increase expected output \( \bar{Q} = \sum \bar{e}_i e_i \). Distortion of this measure is \( \cos \bar{m} \), which \( b_N \) rescales to the extent that \( \overline{M} \neq \overline{\overline{M}} \). Use of an incentive increases expected output because it better aligns employee and firm interests when neither has private information. However, if effort risk aversion is too high or the measure is of low quality, it is conceivable that the optimal incentive is \( b^* = 0 \) (Appendix B).

With autonomy, the optimal incentive is:
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 and the potential for manipulation are 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 than $b^N$ to the extent that $l_i$ and $v_i$ are well aligned, and vice versa. It will be lower to the extent that learning effects on the measure vary more across tasks. This is seen in the last terms in the numerator and denominator in (8).

Appendix C shows that, if learning has similar enough effects on output and the measure ($\sum l_i v_i \geq 0$), the expected effects of granting autonomy – increased learning, output, and disutility of effort – widen with the addition of an incentive. As above, if the measure is highly manipulable this result is not guaranteed, since the employee might exploit this, causing a net loss of profit – output minus incentive pay – to the firm. However, the result holds for any degree of distortion in the measure. For this reason, the optimal incentive is not necessarily larger if the employee is granted autonomy. Moreover, it may not be increasing in the extent of environmental uncertainty $\sigma_k^2$.

If learning improves the evaluation, the likelihood that incentives are used with autonomy rises. Conditional on that, the incentive intensity should then rise with $k$. 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.

"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
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 (e.g., Gibbs, Siemroth & Neckermann 2017). 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, learning will tend to make well-behaved performance measures more effective. Furthermore, empirically we may find a positive correlation between incentive pay and measures of employee GNS.

That said, optimal incentive pay should be designed to rebalance motivation towards output rather than learning, especially if learning is biased. It should not be surprising to observe that incentive pay changes the worker’s focus away from “creative” tasks. 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 this 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. This section provides brief remarks on potential extensions.

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. One would be to analyze the optimal number of tasks to assign to one employee, as sketched above. A deeper model might study the optimal
bundling of tasks based on complementarities in production, skill requirements, or knowledge sharing, resulting in modularity (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 just 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 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 camshaft 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 helpful for 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. 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 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, 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 here 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. Basing some incentive on inputs instead of outputs might rebalance intrinsic motivation that is biased toward learning-intensive tasks. Third, this model might be extended to generate interesting analyses of the dynamics of performance measures.

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 positively correlated with opportunities for learning on the job.

Employees differ in the extent of their intrinsic motivation. The role of GNS 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. There is great interest in how labor market demand for employee characteristics such as cognitive skills, social skills, and creativity 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.

6. Conclusions

Humans are hardwired to learn. Organizational economists have shown increasing interest in policies that foster learning, continuous improvement, and innovation. 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 brings 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 an important motivational component. Including intrinsic motivation should improve our understanding of how organizations can create and use knowledge effectively. Moreover, the most important approach from social psychology fits well with existing approaches in organizational economics.

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 (Ichniowski, Shaw and Pre\-nnushi 1997; Ichniowski and Shaw 2003; Deore, Holzhacker & Krishnan 2021).

The second innovation of the model is to add learning to employee utility. Employees may value learning intrinsically, or it may make the work more interesting. This partially aligns interests. Any professor should find this plausible.

A simple form of autonomy was considered in which the employee can observe and react to varying opportunities for learning. In this model it is optimal to grant autonomy in the absence of incentive pay. That is 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 firm 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 part of the paper considered a simple linear bonus on a single numeric performance measure. Incentive pay serves to rebalance intrinsic motivation towards output. If the measure is not too manipulable, it also complements use of autonomy to foster learning. A number of interesting complications arise when learning affects the employee’s evaluation. If the measure is already well aligned with output, learning may worsen distortion, though in general greater learning is likely to reduce distortion. Learning that is counter-productive for some task increases the employee’s ability to manipulate the measure. In that case optimal incentives might be lower or even zero with autonomy. These are interesting empirical questions.

The model highlights the importance of good job design and performance evaluation to tapping learning-driven intrinsic motivation. The firm can use this effectively if the job generates learning which is motivating to the employee, and simultaneously valuable to the firm. In that case, hiring employees who
are more intrinsically motivated, skilled (especially cognitively), and creative, and giving them more autonomy, are complementary policies that drive knowledge creation. If effective performance measures are available, incentive pay reinforces this, by refining the alignment of interests between an intrinsically motivated employee and the firm. However, learning may make evaluation worse, increase distortion or potential for manipulation of the measure. When that is the case, it may be better to rely on intrinsic motivation instead of incentives. Therefore, many organizational practices related to learning and adaptation that economists have studied may not always require incentive pay.

It is hoped that this paper motivates economists to pay 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 is incomplete without consideration of intrinsic motivation.
Appendix A. Effect of Learning on Performance Measure Distortion

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

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

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

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

(A1) \[
\left( \frac{\mathbf{v}}{M} \right) \cos_{tv} + \left( \frac{\mathbf{l}}{T} \right) \cos_{ml} - \cos_{tm} \left( \frac{\mathbf{l}}{T} \right) \cos_{tl} + \left( \frac{\mathbf{v}}{M} \right) \cos_{mv} \right). \]

The fact that \( \cos_m \leq 1 \) imparts a tendency for this expression to be positive, especially for \( \cos_m \) close to 0. Thus, if a measure is very distorted, a higher rate of learning will tend to make the measure less distorted, while the opposite might be 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 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 \( \mathbf{m} \) has the same length as \( \mathbf{t}, M = T \). 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 \( L = \sqrt{n}l \) 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. 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 \( \cos_{sm} \rightarrow 0 \) (high distortion) the expression becomes positive. As \( \cos_{sm} \rightarrow 1 \) (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.

A similar result holds when learning is biased, but in the same way for the measure as for output, so that \( v_i = \alpha l \). Then \( V = \alpha L, \cos_{sv} = \cos_{st}, \cos_{mv} = \cos_{ml}, \cos_{vl} = 1 \). Maintaining the assumption that \( M = T \), (A1) simplifies to:

\[
\frac{\partial \cos_{tm}}{\partial k} = \left( \frac{L}{T} \right) \left( (\alpha \cdot \cos_{tt} + \cos_{mt}) - \cos_{tm}(\cos_{tt} + \alpha \cdot \cos_{mt}) \right)
\]

\[
= \left( \frac{L}{T} \right) (\cos_{tt}(\alpha - \cos_{tm}) + \cos_{mt}(1 - \alpha \cdot \cos_{tm})).
\]

Once again, as \( \cos_{sm} \rightarrow 0 \) this expression becomes positive, reinforcing the conclusion that if a measure is highly distorted, greater learning mitigates this problem. As \( \cos_{sm} \rightarrow 1 \), this expression will still be positive if \((\cos_{tt} - \cos_{ml})(\alpha - 1) > 0\).

These result are intuitive. 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) is plausible, since the firm chooses the measure to mimic production. This suggests that an increase in the rate of learning will tend to reduce performance measure distortion in practice.
Appendix B. Effect of Adding an Incentive for Expected Output, Learning, and Disutility of Effort

Assume stochastic $\tilde{k}$, and initially that the employee is granted autonomy. Also assume that the performance measure is not very manipulable. A sufficient condition would be that $p_i, v_i \geq \forall i$. A weaker condition is that $\sum q_i p_i, \sum q_i v_i, \sum p_i l_i$, and $\sum l_i v_i$ are all $\geq 0$. The increase in effort when the incentive is added is:

$$\Delta e_i^* = \frac{b \tilde{m}_i}{C} = \frac{b (p_i + \tilde{k} v_i)}{C}.$$  

The change in output from adding an incentive is:

$$\Delta Q = \sum t_i \Delta e_i^* = \sum (q_i + \tilde{k} l_i) \Delta e_i^* = \left( \frac{b}{\tilde{C}} \right) \left( \sum q_i p_i + k \sum (q_i v_i + p_i l_i) + \tilde{k}^2 \sum l_i v_i \right)$$

$$\Rightarrow E\Delta Q = \left( \frac{b}{\tilde{C}} \right) \left( \sum q_i p_i + \tilde{k} \sum q_i v_i + \tilde{k} \sum p_i l_i + E [k^2] \sum l_i v_i \right) \geq 0,$$

given the assumption that $\sum l_i v_i \geq 0$.

The change in expected total learning $E\Delta L$ is the last 2 terms in the last line, which is also $\geq 0$.

The change in the employee’s disutility of effort is:

$$\Delta DU = \left( -\frac{1}{2C} \right) \left( \sum (e_i^* | \text{incentive})^2 - \sum (e_i^* | \text{no incentive})^2 \right) = \left( \frac{-1}{2C} \right) \sum \left( 2\lambda b \tilde{k} l_i \tilde{m}_i + b^2 \tilde{m}_i^2 \right).$$

Some algebra yields the change expected disutility of effort:

$$E\Delta DU = \left( \frac{-1}{C} \right) \sum \left( b^2 p_i^2 + \tilde{k} (2\lambda b p_i l_i + 2b^2 p_i v_i) + E [k^2] (2\lambda b l_i v_i + b^2 v_i^2) \right).$$

The expression inside the summation will generally be positive, except for extreme levels of counter-productive learning, or extremely poor alignment between how learning affects output and the measure. Intuitively this makes sense, as effort will vary more when the employee exploits knowledge about variation in $\tilde{k}$. That raises the expected value of the concave disutility of effort.

A similar result holds if there is no autonomy; replace $E[k^2]$ with $\tilde{k}^2$ throughout. Clearly the same result applies if $k$ is not stochastic.
Appendix C. Effect of Adding an Incentive for Changes in Outcomes When Granting Autonomy

Assume that $\Sigma l_{vi} \geq 0$, which is a weak restriction on the extent of non-productive learning. The difference in effort between the autonomy and no autonomy cases with the incentive is:

$$e_{i}^A - e_{i}^N = \frac{1}{c} \left( \lambda l_i(\bar{k} - \bar{k}) + b(\bar{m} - \bar{m}) \right) = \frac{1}{c} (\lambda l_i + bv_i)(\bar{k} - \bar{k}).$$

Note that the expected value of this is zero. Any increase in expected output from granting autonomy will come from an increase in intertask learning, not from direct marginal products of effort on each task $q_i$.

$$E(Q^A - Q^N) = E\left[ \frac{1}{c} \sum (q_i + \bar{k} l_i)(e_{i}^A - e_{i}^N) \right] = E\left[ \frac{1}{c} \sum \bar{k} l_i(e_{i}^A - e_{i}^N) \right]$$

$$= E(L^A - L^N) = \frac{1}{c} \left( \sum (\lambda l_i^2 + bl_i v_i) \left( E[k^2] - \bar{k}^2 \right) \right) \geq 0.$$

The last term is positive by Jensen’s Inequality. Therefore, if incentive pay is used, expected output and learning are larger with autonomy then without.

The change in the employee’s disutility of effort is:

$$\Delta DU = (-\frac{1}{2}C) \left( \sum (e_{i}^{A})^2 - \sum (e_{i}^{N})^2 \right).$$

Note that $e_{i}^N = E[e_{i}^A]$, and that $e_{i}^A$ is linear and thus convex in $k$. Therefore,

$$E\Delta DU = (-\frac{1}{2}C) \left( E \left[ \sum (e_{i}^{A})^2 \right] - \sum E \left[ (e_{i}^{N})^2 \right] \right) \leq 0,$$

by Jensen’s Inequality. The difference between the employee’s expected disutility of effort with and without autonomy rises when an incentive is added, since the incentive increases the extent to which effort varies with $k$. 

32
Figure 1. Representation of Job Characteristics Model

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


