Specific Knowledge and Performance Measurement

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I examine optimal incentives and performance measurement in a model where an agent has specific knowledge (in the sense of Jensen and Meckling) about the consequences of his actions for the principal. Contracts can be based both on “input” measures related to the agent’s actions and an “output” measure related to the principal’s payoff. Whereas input-based pay minimizes income risk, only output-based pay encourages the agent to use his knowledge efficiently. In general, it is optimal to use both kinds of performance measures. The results help to explain some empirical puzzles and lead to several new predictions.

1. Introduction

Finding the right way to measure performance is one of the most difficult problems that organizations face when designing incentive plans for their employees. In addition to metrics such as sales or earnings that have been traditionally available, advances in information technology and accounting methods have produced a plethora of aggregated and disaggregated measures of performance to choose from (see Ittner and Larcker, 1998). Whereas in theory having more choice is always a good thing, in practice it often appears to raise the chance of getting pay for performance wrong (see, e.g., Greene and Schlesinger, 1991; Fitoussi and Gurbaxani, 2007).

The main guiding principle that the theory of incentives provides is that firms should use all measures that provide incremental information about an agent’s level of effort, subject to the cost of using each measure. Additional complications that may come into play include multitask problems, the manipulation of performance measures, ratchet effects, or the nonverifiability of performance measures.¹ This body of theory has been empirically quite successful, mostly. It is

also well known, however, that firms do not always design incentive contracts in the way theory predicts; see Prendergast (1999), Murphy (1999a), Lafontaine and Slade (2001), and Lambert (2001).

This article studies incentive contracting and the choice of performance measures from a different angle. Its starting point is the observation that agents, be they CEOs or salespeople, usually have unique information about production or about market conditions that in practice is too costly to communicate to others in the firm, and choose their actions based on this information. Indeed, this type of information, termed “specific knowledge” by Jensen and Meckling (1992), is often the reason why agents are entrusted with certain tasks in the first place. As I will show, the simple fact that agents often know a great deal more about how to do their job than do their principals has important consequences for the design of optimal incentive contracts. The insights gained help to explain puzzles in the empirical literature, generate new predictions, and ultimately should be useful for designing compensation plans in practice.

I study a moral-hazard model in which after contracting, but before choosing his actions, the agent receives private information relevant to his efficient choice of actions. This assumption is a departure from standard theory, in which the agent’s action is unobservable but nevertheless predictable because the agent has no private information about what he should be doing. The idea of allowing for postcontractual “hidden information” is hardly new, and is conceptually straightforward. The challenge, instead, has been to find a tractable framework within which one can derive predictions about the role of specific knowledge for incentive contracting and performance measurement. This article attempts to fill this gap.

The basic argument of the article is simple: if an agent has specific knowledge about how his actions contribute to the principal’s payoff, then the best way to get him to use his knowledge in choosing his actions is to provide incentives based on the principal’s payoff or another closely correlated measure of “output.” Because output measures are subject to random influences outside the agent’s control, however, output-based pay exposes the agent to income risk, for which the agent must be compensated if he is risk averse or wealth constrained. Weighing the benefits and costs of incentive pay then leads to the prediction that the more valuable the agent’s specific knowledge for the principal, the greater are the optimal incentives for the agent.

In addition to paying for output, it is often also possible to pay an agent based on “input” measures that are closely correlated with the agent’s actions and to a lesser extent subject to noise. For instance, for a salesperson, input measures might include hours worked, number of customers contacted, new accounts created, quality of advice, and so forth; measures of output might be sales or profit (see Section 2 for more examples). The agent’s specific knowledge can then be interpreted as knowledge of how different inputs translate into output.

When both input and output performance measures are available, we obtain the following tradeoff. An incentive contract based on some formula combining input measures minimizes the agent’s income risk, but does not give the agent much incentive to use his specific knowledge; instead, his actions are largely determined by the compensation plan. Output-based compensation, in turn, gives the agent an incentive to use his knowledge in the most productive way, but also exposes the agent to greater income risk. In the optimal incentive contract, the weights on input-versus output-based pay are chosen to strike a balance between the dual goal of minimizing income risk and maximizing the utilization of valuable knowledge.

More formally, in my model (see Section 3), the principal faces technological uncertainty about the productivity of the agent’s effort. The agent receives a private signal about his productivity, which he is unable to communicate to the principal. For simplicity, I take the existence of specific knowledge as given; that is, I am not concerned with information acquisition

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2 Technically, a model in which the agent chooses his actions based on (postcontractual) private information is still a moral-hazard model in the sense that the agent chooses a joint distribution of performance measures and outcomes; cf. Holmström and Milgrom (1987).

3 For many jobs, of course, useful output measures are unavailable, leaving the firm with no alternative but to measure input in some way; cf. Fama (1991).
(see, e.g., Demski and Sappington, 1987) or communication (see Dessein, 2002). After receiving his information, the agent chooses his effort. The agent is risk neutral but protected by limited liability; it is therefore costly for the principal to expose the agent to risk. The principal can compensate the agent based on verifiable information about the agent’s effort (i.e., his input), and on a noisy measure of output. I refer to the extent of noise in measuring output as environmental uncertainty (or risk).

There exists a closed-form solution for the optimal compensation contract (Section 4). When there is no technological uncertainty, or when the agent has no private information about it, the principal prefers input-based pay because output-based pay is risky. In contrast, if the agent’s private information is sufficiently valuable, it is optimal to pay the agent at least partially for output, even if effort can be measured perfectly. This result already explains a puzzling observation in the empirical literature, which is that compensation is often based on noisy output measures even when good input measures are available (Murphy, 1999a; Ittner, Larcker, and Meyer, 2003).

The optimal relative weight on output-based pay, the principal’s expected profit, and the agent’s expected wage all increase with the agent’s level of knowledge, the extent of technological uncertainty, and the expected productivity of the agent’s effort; see Section 4. Intuitively, all of these changes in the environment amount to increases in the value of the agent’s knowledge. The weight on output-based pay increases with technological uncertainty but decreases with the level of environmental risk. Section 4 relates these results to a current literature on the relation between risk and incentives; see also below.

In Section 5, I extend the basic model to one in which the agent performs two tasks instead of just one. In the two-task model, both the level and the allocation of effort across tasks matter. By allowing the agent to choose what to work on, this model better captures the idea of managers as “decision makers” than does the single-task model. I show that all results of the basic model generalize to this case.

Section 6, finally, discusses a wide range of implications of the theory. Specifically, I develop predictions about how optimal incentives and the choice of performance measures depend on the knowledge gap between principal and agent, a firm’s growth options, the rate of change in an industry, job complexity, and corporate governance, and discuss possible empirical measures for the variables of the model.

Of broader relevance here is the observation that the extent to which a firm relies on strong incentives (loosely, output-based pay) or on monitoring through different governance mechanisms (loosely, input-based pay) should depend on the knowledge gap between the CEO and his monitors. Thus, for instance, a coincidence of high CEO pay and “weak” governance may be part of an optimal contract when the CEO has considerable specific knowledge, and need not be a consequence of managerial entrenchment as has been suggested in the literature.

Specific knowledge has always played a key role in a large literature that examines the delegation of decisions to agents. One strand of this literature focuses on agents who must be given incentives to acquire information relevant to a decision; see Demski and Sappington (1987) for an early analysis and Malcomson (2004) for a recent one. This literature typically assumes that the agent has no direct stake in the decision he takes. In my model, instead, the agent acquires information about how to best allocate his effort for free, but must be given incentives to use his knowledge efficiently.

A second strand of the delegation literature examines the principal’s choice of whether to delegate a decision to the agent; see Aghion and Tirole (1997), Dessein (2002), Stein (2002), Marino and Matsusaka (2003), and Alonso and Matouschek (2008). Many of these papers also

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4 I abstract from problems with measuring certain tasks; cf. Holmström and Milgrom (1991). The main insights of the article, however, remain valid even when multitask measurement problems exist.

5 As a referee pointed out, because input-based pay does not provide incentives to use specific knowledge, it also undermines incentives to acquire knowledge. Output-based pay therefore likely also helps to provide incentives for information acquisition.
allow for communication from agent to principal. A natural feature of these models is that
delegation is more likely the better informed the agent is; see, for example, Dessein (2002).
The same holds in my model, but as the link between specific knowledge and delegation is
well known, I will not emphasize it. Instead, my focus is on the properties of the optimal
incentive contract conditional on delegation, whereas the papers mentioned typically abstract
from monetary incentives.

A third strand of the delegation literature looks at situations in which an agent is motivated
by career concerns (that is, his reputation as an expert) instead of by money or private benefits.
As some papers have shown, the observability of an agent’s actions (“inputs”) on top of observed
outcomes can lead to distorted decisions by the agent. It may then be preferable to obscure the
observation of the agent’s actions; see Prat (2005) and Fingleton and Raith (2005).

The closest precursor to this article is Prendergast (2002), where a principal delegates the
choice of a project to a privately informed agent if the projects’ payoffs are more uncertain.
Delegation goes along with the provision of output-based incentives to induce the right project
choice. This generates a positive correlation between uncertainty (risk) and the provision of
incentives, which stands in contrast to standard incentive theory but is consistent with much
of the evidence. Related papers include Baiman, Larcker, and Rajan (1995), Lafontaine and

In contrast to Prendergast (2002), my article focuses on incentive contracts and not
delegation. It applies to situations in which an agent’s authority over a wide range of decisions is
more or less given but where the principal must choose how to measure performance, as is the
case for many managerial positions. Second, both Prendergast and related papers are primarily
concerned with identifying conditions under which incentives should be positively or negatively
related to risk. Although my model speaks to this question, its results suggest that the relation
between risk and incentives is too subtle to be of much use for the design of compensation plans
in practice; hence my focus on other implications of specific knowledge. The papers mentioned
also exemplify the analytical hurdles one faces when trying to incorporate specific knowledge
into models of incentive contracting: most employ models that are either not very tractable or
rely on nonstandard assumptions.6

In Baker (1992), the agent has private information about how his effort affects measured
performance. Baker shows that the less measured performance is correlated with the principal’s
true payoff, the greater is the agent’s incentive to “game the system.” The principal’s response
is then to provide weaker incentives in order to curb the agent’s use of his information. Here,
in contrast, distortions play no role; the agent’s private information is useful for the principal.
The principal therefore wants the agent to use his information, which is the opposite of Baker’s
prediction.

Finally, it has been argued that firms often face a tradeoff between performance measures that
involve little risk for the agent but are distorted, and measures that are aligned with the principal’s
objectives but are noisy. But the agent’s knowledge either plays no role in this argument (see
Feltham and Xie, 1994; Baker, 2000, 2002; Datar, Kulp, and Lambert, 2001), or is the cause
of distortions (Baker, 1992; Baker, Gibbons, and Murphy, 1994). In any case, dysfunctional
responses to input-based pay result from the firm’s inability to measure everything that matters,
and can in principle be remedied by looking for more and better performance measures. That is
precisely what many companies have done in recent years, only to realize that they simply do
not know very well how their employees’ actions contribute to firm performance, whereas the
employees often have a much better idea. This is the problem studied here.

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obtain some comparative-statics results but no closed-form solutions. Baiman, Larcker, and Rajan (1995), Lafontaine and
Bhattacharyya (1995), and Shi (2008) use numerical simulations. Prendergast’s (2002) model is more similar to Aghion
and Tirole (1997) than to models in the tradition of Holmström.
2. Inputs, outputs, and knowledge: applications

The distinction between “input” and “output” measures of performance itself is not new. Instead, it is the idea that the agent has specific knowledge about how inputs map into output which renders a new and useful way to think about the choice among performance measures.

Consider the problem that McDonalds faced in the early 1970s of how to compensate managers of company-owned restaurants (Sasser and Pettway, 1974). One option was to use traditional financial metrics such as sales or profits. Another was to base compensation on operational measures of “quality, service, and cleanliness” (QSC) obtained by restaurant inspectors, which the company considered to be the key inputs under the control of managers. These performance measures differ not only in that QSC is an input under a manager’s control whereas profit is an output subject to noise. Most likely, a restaurant manager also has specific knowledge about how the mix of quality, service, and cleanliness translates into profit. It is for this reason that the company may want to base pay on output (and to a degree that depends on the manager’s knowledge) even if it exposes the manager to more risk. In contrast, if the functional relation between QSC and profit were known, it would be unambiguously optimal to base pay on QSC.

Likewise, for many other jobs, there are multiple performance measures that can be meaningfully ranked along an input-output continuum. Salespeople can be compensated based on the sales or profit they generated (output), but also on very detailed input measures such as new accounts created, hours worked, number of items sold in certain product categories, and so forth.\

For division managers of larger firms, “output” is often best captured by (accounting) measures of division profit, whereas “inputs” may include a variety of operational measures. Alternatively, when managers are compensated based on the performance of their own unit as well as that of a larger group (e.g., the entire firm), one can think of the former as an input and the latter as an output; see Hwang, Erkens, and Evans (2006) for further development of this argument.

CEO compensation is based on both stock prices and accounting (e.g., earnings) measures. Stock price is usually the better measure of firm value, but is also influenced by many factors outside a CEO’s control. Accounting measures, on the other hand, are less closely related to firm value but are more under the CEO’s control because “managers understand and can ‘see’ how their day-to-day actions affect year-end profitability” (Murphy, 1999a). One can therefore think of stock price as output, and accounting measures as inputs, even though the latter are highly aggregated measures too. If CEOs have specific knowledge of how they contribute to firm value, then shareholders face a tradeoff between undistorted but risky stock-based compensation, and compensation based on other measures that is less risky but also gives CEOs less incentives to use their knowledge to maximize firm value.

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7 In line with the argument of this article, Hauser, Simester, and Wernerfelt (1994) argue that basing compensation on customer satisfaction may be desirable, especially when a salesperson knows better than the firm how his actions contribute to long-run profits.

8 Not all nonfinancial measures are inputs, though. For example, market share would hardly be considered an “input” relative to (output) measures such as share price or earnings.

9 Ittner and Larcker (1998) document an increase over time in the use of nonfinancial in addition to the more traditional financial performance measures. Ittner, Larcker, and Rajan (1997) study the determinants of the use of financial and nonfinancial measures, testing hypotheses derived from the Informativeness Principle.

10 See also Sloan (1993), who argues that firms’ use of accounting measures in addition to stock price can be understood as a way to shield CEOs from market risk.

11 Similar arguments apply to the distinction between economic value added (EVA), an aggregated accounting measure, and “balanced scorecards,” which provide a wide array of financial and nonfinancial performance measures. Both have been advocated as performance measures for executives, but using scorecards for compensation is problematic if an executive has specific knowledge about how different scores translate into profit.
3. Model

Consider a moral-hazard model involving a principal and an agent:

**Production:** Output, denoted $Y$, is stochastic and can be either 0 or 1. The probability that $Y = 1$ is given by $\min\{\theta a, 1\}$, where $a$ is the agent’s effort and $\theta$ is the productivity of effort.

**Technological uncertainty:** The productivity of effort, $\theta$ is either high ($\theta_H$) or low ($\theta_L$) with equal probability, where $\theta_H, \theta_L = (1 \pm t)\bar{\theta}$. The parameter $\bar{\theta}$ is the expected marginal benefit of effort; $t \in [0, 1]$ measures the degree of technological uncertainty. (Many of the model’s parameters are normalized between 0 and 1 or $-1$ and 1, which significantly simplifies calculations.)

**Information about $\theta$:** The principal knows the distribution but not the realization of $\theta$. The agent receives a private signal $s \in s_H, s_L$ about $\theta$. The probabilities $\Pr(s_H | \theta_H)$ and $\Pr(s_L | \theta_L)$ are given by $(1 + k)/2$, where $k \in [0, 1]$ captures the quality of the agent’s knowledge. The agent cannot communicate $s$ to the principal.

The productivity $\theta$, and the agent’s specific knowledge about it, should be interpreted broadly. It may represent information about the firm’s production technology, market conditions, or optimal responses to changes in those conditions. All that matters is that the agent has specific knowledge relevant to his (first-best) choice of $a$, which is what the multiplicative term $a\theta$ is meant to capture.

**Agent’s utility:** The agent is risk neutral, but protected by limited liability, which is a combination of assumptions economically similar to risk aversion. The agent’s utility is $w - da^2/2$, where $w$ is his total compensation (described below) and $da^2/2$ is the disutility of effort scaled by the parameter $d$.

**Performance measurement:** As discussed in Section 2, the distinction between inputs and output can be interpreted very broadly. But as the role of measurement error for the design of optimal contracts is well known (see Prendergast, 1999; Lafontaine and Slade, 2001), there is no loss of generality in assuming that one performance measure is effort itself, and the other a noisy measure of output. As we will see, even if effort can be perfectly measured, basing compensation on risky output measures is generally desirable when the agent has specific knowledge.

Thus, I assume that the agent’s effort $a$ can be measured without noise and is contractible. Output, however, can be measured only imperfectly by a contractible variable $y$ that takes the values 0 or 1. The probability that $y = Y$ is given by $1 - e/2$, where $e \in [0, 1]$ is a measure of environmental uncertainty or risk: if $e = 0$, $y$ measures $Y$ perfectly, whereas if $e = 1$, $y$ is entirely uninformative. I assume that $e > 0$, because for $e = 0$ there is no reason to use $a$ as a performance measure and the results of the model are trivial. For $\theta a \in [0, 1]$, the expected value of $y$ conditional on $\theta$ and $a$ is given by

$$E[y(\theta, a)] = \frac{e}{2} + (1 - e)\theta a.$$  

(1)

Note from (1) that although environmental risk does not affect the true productivity of the agent’s effort, it does reduce the responsiveness of measured performance to the agent’s effort. This is a standard feature of any moral-hazard model with only two possible outcomes (see, e.g., Laffont and Martimort, 2001), but stands in contrast to, for example, the model of Holmström and Milgrom (1987, 1991).\(^{12}\)

**Compensation:** I confine attention to contracts that are linear in both $a$ and $y$; that is, the agent’s total compensation is given by

\[^{12}\] Another source of uncertainty in addition to technological and environmental uncertainty is of course the randomness of $Y$ itself. This randomness, however, is merely a convenient way to map continuous actions into two outcomes. It is irrelevant for the results because both principal and agent are risk neutral and therefore only care about the expected value of $Y$. 

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\[ w = \alpha + \beta_{in} a + \beta_{out} y. \]  

(2)

The restriction to linear contracts is standard, and is motivated by their use in practice. The assumption that \( a \) itself is contractible is a simplification; in reality, “input” is typically a noisy measure of effort. This is why I assume that the principal pays a piece rate for effort instead of using, for example, a forcing contract (it will become clear that a forcing contract would not be optimal anyway).

Limited liability means that the agent’s compensation must be nonnegative for any effort level and any realized output (although realized utility may be negative). Because both \( a \) and \( y \) can be zero, this means that the salary \( \alpha \) must be nonnegative. As is standard in models with limited liability, I assume that the agent’s participation constraint is not binding; therefore, we can without loss of generality set \( \alpha = 0 \).

Timing:

(i) The principal offers a contract \((\beta_{in}, \beta_{out})\); the agent accepts or rejects.
(ii) The productivity \( \theta \) is realized.
(iii) The agent receives a signal \( s \) about \( \theta \).
(iv) The agent chooses effort \( a \).
(v) The output \( Y \) and the measured performance \( y \) are realized, and the agent is compensated accordingly.

4. The optimal contract and its properties

- **Optimal incentive contract** To keep the calculations simple and avoid case distinctions, I restrict the analysis to parameters that lead to interior solutions for all endogenous variables. Necessary and sufficient conditions are

\[
\begin{align*}
(a1) \quad 2k^2t^2\bar{\theta}^2 > & \frac{de}{1 - e}, \quad \text{and} \\
(a2) \quad 4(1 - e)ktd - (1 + t)(2(1 - e)k)(1 + kt)\bar{\theta}^2 - de > 0.
\end{align*}
\]

Condition (a1) imposes a lower bound on the quality of the agent’s knowledge \( k \), and guarantees an interior solution for \( \beta_{out} \). Condition (a2) guarantees that \( \theta a \) does not exceed 1.\(^{13}\)

The analysis of the game is very simple. In the fourth stage of the game, the agent chooses his effort based on his beliefs about \( \theta \), denoted \( \hat{\theta} \), to maximize

\[
\beta_{in} a + \beta_{out} E(\gamma | \hat{\theta}, a) - d a^2 = \beta_{in} a + \beta_{out} \left( \frac{e}{2} + (1 - e)\hat{\theta} a \right) - d a^2,
\]

the solution to which is

\[
a = \frac{1}{d}[\beta_{in} + (1 - e)\beta_{out}\hat{\theta}].
\]

(3)

(4)

What is left to do is to compute \( \hat{\theta} \) (as function of the signal \( s \)), plug (2), (1), and (4) into the principal’s profit \( Y - w \), and take expectations over the joint realizations of \( \theta \) and \( s \). Maximizing the resulting expected profit over \( \beta_{in} \) and \( \beta_{out} \) leads to the following result:

**Proposition 1.** Under conditions (a1) and (a2), the optimal contract parameters are given by

\[
\beta_{in}^* = \frac{de}{4(1 - e)k^2t^2\bar{\theta}} \quad \text{and} \quad \beta_{out}^* = \frac{1}{2(1 - e)} - \frac{de}{4(1 - e)k^2t^2\bar{\theta}^2}.
\]

(5)

The resulting expected equilibrium effort is \( E(a) = \bar{\theta}/(2d) \), which is half of the expected first-best effort level conditional on the agent’s knowledge. The expected profit for the principal is given by

\(^{13}\)The existence of parameter sets that satisfy both conditions can be seen by example; choose, for example, \( d = 1, \bar{\theta} = 1, k = .8, t = .6 \), and \( e = .2 \).
The agent’s expected wage is given by

\[ E(w) = \frac{4(1-e)^2k^2t^2(1+k^2t^2)\bar{\theta}^4 + d^2e^2 - 4de(1-e)k^2t^2\bar{\theta}^2}{16d(1-e)^2k^2t^2\bar{\theta}^2}. \]  

(6)

Proof. See the Appendix.

At one extreme, when pay is only input based \((\beta_{in} > 0, \beta_{out} = 0)\), the agent’s effort depends only on \(\beta_{in}\) and not on \(\hat{\theta}\) (cf. (4)). Thus, the agent has no incentive to use his specific knowledge; the equilibrium effort is fully determined, very much like in standard models of incentive contracting. At the other extreme, purely output-based pay \((\beta_{in} = 0, \beta_{out} > 0)\) is costly for the principal whenever \(e > 0\): the more measured performance is affected by noise, the less it is affected by effort; cf. (1). To induce a certain level of effort, the principal therefore has to pay a higher reward for a good outcome. Because the reward for a bad outcome is bounded from below at zero, greater risk is costly for the principal.\(^\text{14}\)

Thus, the key tradeoff is that input-based pay is riskless but fails to make use of the agent’s information, whereas output-based pay encourages the optimal use of information but is risky and hence costly for the principal. When technological uncertainty and the agent’s specific knowledge are sufficiently important, the optimal incentive contract is partly input and partly output based. It is straightforward to derive the optimal bonus \(\beta_{out}^*\) when input cannot be measured.

Proposition 1 already helps to explain one of the puzzles in the empirical literature. In a wide range of occupations, be it salespeople, franchisees, or executives, incentive pay is based largely on aggregate financial data and only partly on operational measures or other measures of “input”; see Murphy (1999a) and Ittner, Larcker, and Meyer (2003). The puzzle here is that the Informativeness Principle would suggest greater reliance on input measures as more precise measures of effort.

One reason for using output-based pay, of course, may be a lack of good input measures. As Baker (2002) has pointed out, principals often face a tradeoff between noisy performance measures that are closely correlated with the principal’s payoff (i.e., output measures) and less noisy but distorted input measures. Unless the agent’s input can be measured quite well, there may be little choice but to base compensation on output.

But this cannot be the whole story. Firms nowadays often have an abundance of information about the minutiae of their employees’ activities, through the use of activity-based costing, balanced scorecards, and integrated information systems. Although measurement problems continue to matter in many occupations, substantial progress has been made in measuring almost all relevant dimensions of performance of, for instance, salespeople or managers. Still, even firms that go to great trouble to measure employees’ inputs find it difficult to use these measures in their compensation plans.

Even if all of an agent’s actions can be perfectly measured, the problem remains of how to weight each measure in a compensation plan. Firms simply do not know very well how their employees’ actions contribute to firm performance, whereas the employees often know a great deal more. The best solution then is to base compensation at least partly on output, as stated in Proposition 1.

\[ \Box \] Determinants of the optimal contract. The equilibrium variables of Proposition 1 depend on the model’s parameters as follows:

\(^{14}\) Whereas in the model of Holmström-Milgrom (1987), risk affects the agent’s participation constraint but not his incentive constraint, in general it affects both constraints. With a risk-neutral agent and limited liability, risk affects only the incentive constraint. See also Laffont and Martimort (2001).
Proposition 2.

(a) $\beta^*_\text{out}$ is increasing in $k$, $\bar{\theta}$, and $t$. It is decreasing in $d$, and decreasing in $e$ if $\partial E(y) / \partial e \geq 0$. That is, compensation is more sensitive to output the greater the agent’s knowledge, the expected productivity of effort, or the technological uncertainty, and less sensitive to output the greater the agent’s disutility parameter. If expected measured output is increasing in risk, then compensation is less sensitive to output the greater the level of risk.

(b) $\beta^*_\text{in}$ is decreasing in $k$, $\bar{\theta}$, and $t$, and increasing in $d$ and $e$. That is, compensation is less sensitive to inputs the greater the agent’s knowledge, the expected productivity of effort, or the technological uncertainty, and more sensitive to inputs the greater the agent’s disutility parameter or the level of risk.

(c) $E(\pi)$ and $E(w)$ are increasing in $k$, $\bar{\theta}$, and $t$, and decreasing in $d$ and $e$. That is, the principal’s expected profit and the agent’s expected wage are higher the greater the agent’s knowledge, the expected productivity of effort, or the technological uncertainty, and lower the greater the agent’s disutility parameter or the level of risk.

Proof

See the Appendix.

The results for $\beta^*_\text{out}$ are the same if only output-based compensation is feasible. Notice that changes in all parameters except $e$ lead to changes in $\beta^*_\text{in}$ and $\beta^*_\text{out}$ in opposite directions. This allows us to make unambiguous predictions about the optimal relative weights placed on input and output performance measures; see Section 6.

The intuition for the knowledge parameter $k$ is straightforward: the more important the agent’s knowledge, the higher the optimal $\beta_{\text{out}}$ and the lower $\beta_{\text{in}}$, that is, the more the agent’s wage is based on output. Better knowledge also translates into a higher equilibrium total surplus between principal and agent, and under the optimal contract both parties share the surplus gain (part c). For most other parameters, too, the general intuition is that a parameter change will lead to a shift toward output-based pay, higher profit, and a higher wage if and only if the change raises the value of the agent’s information.\footnote{This can be formalized as follows. Define the social value of knowledge $v$ as the difference between the total surplus when an agent with knowledge $k$ chooses the first-best effort, and the analogous surplus for an agent with no specific knowledge. Then one can show that the weight on output-based pay and the principal’s profit are increasing in $v$, and vary with most parameters only through $v$. I would like to thank Meg Meyer for suggesting this generalization.}

For instance, as $\bar{\theta}$ scales the productivity of effort, a higher value of $\bar{\theta}$ is associated with a higher value of the agent’s knowledge about how to allocate his effort. It follows that the relative weight on output-based pay and the principal’s profit are increasing in $\bar{\theta}$. A higher $t$ implies a greater variance of the tasks’ productivities, which makes it more valuable for the principal to rely on the agent’s knowledge about them.

The results for environmental risk ($e$) are familiar from standard agency models (see also footnote 14): the greater the noise in measuring output, the lower the optimal weight on output in the incentive contract, and the lower the principal’s profit. To understand the qualifying condition for $\beta^*_\text{out}$ in part (a), notice that a change in $e$ affects the variance of $\nu$, but therefore also (as in any model with only two possible outcomes) its expected value. Other things equal, the principal would want to decrease $\beta_{\text{out}}$ if $E(y)$ increases, and vice versa. The question then is what happens when $\partial E(y) / \partial e = 0$. Part (a) states that in this case, an increase in $e$ unambiguously leads to a decrease in $\beta_{\text{out}}$. This effect is reinforced for higher values of $e$, where $E(y)$ is increasing in $e$, whereas for smaller values it may be outweighed by the upward adjustment of $e$ because of a decrease in $E(y)$.

Because of the great attention the literature has paid to the relation between risk and incentives, some remarks about this relation in the context of my model follow next. A detailed discussion of more novel implications of Proposition 2 appears in Section 6.

□ Uncertainty versus incentives revisited. A central prediction of principal-agent theory is that a risk-neutral principal provides weaker incentives to a risk-averse agent the more the
performance measure is affected by noise. Although studies supporting this prediction (e.g., Aggarwal and Samwick, 1999) are well known, Prendergast (2002) concludes that they are greatly outnumbered by studies finding a positive or insignificant relation between risk and incentives. This discrepancy between theory and evidence has attracted much interest in recent research.

One reason for the discrepancy may be that agents have knowledge about uncertain events and must be given incentives to use it, an idea first modelled by Prendergast (2002). The present model distinguishes explicitly between uncertainty that affects the agent’s optimal choices, and uncertainty in the measurement of performance. Whether one should expect to see a positive or a negative relation between incentives and risk then depends on which type of uncertainty is affected relatively more strongly. According to Proposition 2, $e$ affects the optimal incentive contract and the principal’s profit in ways familiar from standard agency models (see also footnote 14): the greater the noise in measuring output, the lower the optimal weight on output in the incentive contract, and the lower the principal’s profit.

An increase in $t$, on the other hand, implies a greater value of the agent’s knowledge and increases the principal’s profit (part c). This result is similar to Prendergast’s prediction that risk and incentives are likely to be positively related if delegation decisions are not controlled for (e.g., if company-owned and franchised outlets of a chain are pooled). Parts (a) and (b) of the proposition, however, imply that even when delegation of decision rights is taken as given (an appropriate assumption for most managerial occupations), incentives and uncertainty may be positively related. These results stand in contrast to Prendergast’s argument that controlling for delegation, incentives, and risk should be negatively related for the usual reasons.

Two conditions are responsible for the positive relation between technological uncertainty and (output-based) incentives: first, $\theta$ influences the agent’s individually optimal choice of effort. This condition is necessary because exposing the agent to risk is always costly for the principal and leads to weaker incentives unless the realized state of nature is relevant for the agent’s actions. Second, the agent’s information pertains to the true productivity of his effort and thus affects his first-best effort. What the agent cares about is measured performance $y$, but $y$ depends on $\theta$ only through its effect on $Y$. Thus, the agent’s use of his information always benefits the principal. If, in contrast, the agent’s information pertains to measured performance instead of true productivity, its use is usually detrimental to the principal. Consequently, a higher variance of the performance measure is typically associated with lower optimal incentives; see Baker (1992) and Baker, Gibbons, and Murphy (1994). More generally, whether or not an agent’s use of his information is beneficial for the principal depends on the precise correlation structure between the agent’s information, the productivity of effort, and measured performance.

The above discussion suggests that there are serious obstacles to studying the empirical relation between incentives and risk, a conclusion supported by the current state of the literature. The main problem is that whereas technological and environmental uncertainty are separate entities in this (reduced-form) model, in reality they are often correlated. For example, for the CEOs of oil companies, oil price fluctuations may call for appropriate actions based on the CEOs’ expertise, but also affect the companies’ performance for reasons unrelated to any actions taken. Whether incentives ought to be negatively or positively related to a certain source of risk thus depends on how important responses to that risk are, which is bound to be difficult to ascertain for researchers (see Shi, 2008, for one approach to resolve this problem). It is tempting to conclude that the relation between risk and incentives is too subtle to be of much use for the design of incentive plans in practice.

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16 See also Demsetz and Lehn (1985): “In less predictable environments, however, managerial behavior . . . figures more prominently in a firm’s fortunes. . . . Hence, noisier environments should give rise to more concentrated ownership structures.”

17 For further discussion, see Bushman, Indjejikian, and Penno (2000). See also Lizzeri, Meyer, and Persico (2002), who show that interim performance evaluation of an agent is bad for the principal when the agent’s productivity is known, and hence evaluation only informs the agent about measured performance rather than socially optimal actions. In contrast, interim evaluation can be useful when there is uncertainty about the agent’s productivity.
5. Two tasks

Suppose now the agent performs two tasks. The principal now cares not only about the agent’s level of effort but also about how effort is allocated. Introducing this additional dimension of choice helps capture the notion of managers as decision makers as opposed to agents who simply need to be induced to work hard. I will introduce some new notation and additional parameters; otherwise, everything is the same as in the one-task model.

Production: The output \( Y \) is again either 0 or 1; the probability that \( Y = 1 \) is given by \( \{a_1 \theta_1 + a_2 \theta_2, 1\} \), where \( a = (a_1, a_2) \) is the agent’s effort exerted on the two tasks, and \( \theta = (\theta_1, \theta_2) \) is a vector of productivities.

Technological uncertainty: The productivity \( \theta_i \) of each task \( i \) is given by \( \theta_i = (1 + t)\tilde{\theta} \) as before. The \( \theta_i \) may be correlated; the probability that \( \theta_1 = \theta_2 \) is given by \( (1 + \rho)/2 \) for \( \rho \in [-1, 1] \). When \( \rho = 1 \), the model in effect collapses to the one-task model. When \( \rho = -1 \), the total productivity of effort across tasks is always constant but is concentrated on one task or the other.

Information about \( \theta \): As before, the principal knows the expected productivity \( \tilde{\theta} \), but not the realization of \( \theta \). The agent receives a private signal \( s = (s_1, s_2) \) about \( \theta \); the probability that \( s_i = \theta_i \) is given by \( (1 + k)/2 \). The conditional variables \( s_i | \theta \) are independent, and so \( s_1 \) and \( s_2 \) are correlated only indirectly through the correlation between \( \theta_1 \) and \( \theta_2 \).

Agent’s utility: The agent’s utility is \( w - d(a) \); the disutility \( d(a) \) is given by

\[
d(a) = \frac{d}{1 + \phi} (a_1^2 + a_2^2 + 2\phi a_1 a_2).
\]

The parameter \( \phi \) is constrained to the interval \((-1, 1]\) and measures the substitutability of tasks for the agent. If \( \phi = 1 \), the tasks are perfect substitutes for the agent in the sense that \( d(a) \) reduces to \( d(a_1 + a_2)^2/2 \). If \( \phi < 0 \), the tasks are complements in the sense that spending more effort on task \( i \) reduces the disutility of spending effort on task \( j \neq i \). As \( \phi \) converges to \(-1\), \( d(a) \) converges to \( d(a_1 - a_2)^2/2 \). If \( a_1 = a_2 = a \), then \( d(a) \) reduces to \( 2da^2 \). Thus, scaling the disutility by \( 1/(1 + \phi) \) ensures that changes in \( \phi \) affect the interaction \( \partial^2 d(a)/(\partial a_1 \partial a_2) \) but not the level of disutility for equal levels of effort on each task.

Performance measurement and compensation: Compensation can be based on both \( a \) and a noisy measure of output \( y \), which relates to true output \( Y \) in the same way as above. Hence, for \( \theta_1 \) \( a_1 + \theta_2 \) \( a_2 \in [0, 1] \), the expected value of \( y \) conditional on \( \theta \) and \( a \) is given by

\[
E[y(\theta, a)] = \frac{e}{2} + (1 - e)(\theta_1 a_1 + \theta_2 a_2). \tag{8}
\]

Contracts are restricted to be linear; the agent’s total compensation is given by

\[
w = \alpha + \beta_{1a}(a_1 + a_2) + \beta_{\text{out}} y.
\]

Again, we can set \( \alpha = 0 \). The use of the same piece rate for \( a_1 \) and \( a_2 \) is not a restriction but follows as a result from the symmetry of the model. The timing of the game is the same as before.

Aside from introducing the new and interpretable parameters \( \rho \) and \( \phi \), the two-task version of the model helps to clarify the relation between “effort” in models of incentive contracting and “decision making” in models of delegation. What is limiting about standard incentive models is not the notion of effort itself, but the absence of specific knowledge. Once it is incorporated into the model, the distinction between effort and decision making reduces to “how much” versus “what.” In either case, an optimal compensation plan balances the same two goals: to shield the agent from income risk, and to align his incentives with the principal’s objectives.

The model introduced here fits both interpretations. If \( \rho = 1 \), only the level of effort but not its allocation matters. The opposite case, \( \rho = -1 \), can be interpreted as a situation where the agent must choose between two projects, and exactly one is profitable. With perfect knowledge \( (k = 1) \), the agent then chooses one of two (symmetric) effort allocations, which can be interpreted
as choosing one of the projects. With less than perfect knowledge, the agent will generally hedge his bets and invest in both projects (depending on the information he receives), but that does not affect the interpretation.\footnote{Note, though, that if \( k < 1 \), then the agent’s total effort is not constant even if \( \rho = -1 \), but depends on his signals \((s_1, s_2)\) and not just \( \theta \). Thus, there is still a “vertical dimension” to the agent’s choice of \( a \) in addition to the “horizontal” allocation between the tasks. See also the discussion at the end of Section 4.}

To express the optimal contract in a compact form, define

\[
\eta = \frac{2(1 - \phi)\rho(1 - k^2\rho) + (1 - \rho)^2(1 + k^2\phi\rho)}{1 - k^4\rho^2}.
\] (9)

I focus again on an interior solution for the optimal contract; the precise conditions (which look similar to (a1) and (a2) above) are stated in the proof of the next result.

**Proposition 3.** An interior solution for the optimal contract is given by

\[
\beta_{in}^* = \frac{(1 - \phi)de}{4(1 - e)k^2t^2\eta\theta} \quad \text{and} \quad \beta_{out}^* = \frac{1}{2(1 - e)} - \frac{(1 - \phi)de}{4(1 - e)k^2t^2\eta\theta^2}.
\] (10)

**Proof** See the Appendix (which also proves existence by an example).

The intuition for this result is the same as for Proposition 1: the levels of \( \beta_{in} \) and \( \beta_{out} \) jointly determine the level of the agents’ effort, whereas the relative weights on \( \beta_{in} \) and \( \beta_{out} \) balance the dual objectives of getting the agent to use his knowledge and minimizing his rent due to limited liability. Like in Section 3, it is straightforward to derive an optimal output piece rate \( \beta_{out}^* \) when output is the only available performance measure.

**Proposition 4.** All results of Proposition 2 carry over to the two-task model. In addition,

(a) \( \beta_{out}^* \) is decreasing, \( \beta_{in}^* \) is increasing, and \( E(\pi) \) and \( E(w) \) are decreasing in \( \rho \) if and only if

\[
k^2\phi(1 - \rho^2)(1 - k^4\rho^2) + 2(1 - k^2)[\phi(1 - k^2\rho^2) - \rho(1 - k^2)] \geq 0.
\] (11)

There exists \( \tilde{\rho} \in (0, 1) \) such that (11) holds if and only if \( \rho \leq \tilde{\rho} \). A sufficient condition for (11) to hold is that \( a_1(\theta) \) is larger when the agent obtains a low signal on task 2 than when he obtains a high signal.

In words, compensation is less sensitive to output and more sensitive to input, and the expected profit and wage are lower, the more correlated the task productivities are, provided that they are not already highly correlated. A sufficient condition is that a low signal on one task leads to higher effort on the other task (as opposed to lower effort on both tasks).

(b) \( \beta_{out}^* \) is increasing, \( \beta_{in}^* \) is decreasing, and \( E(\pi) \) and \( E(w) \) are increasing in \( \phi \). That is, compensation is more sensitive to output and less sensitive to inputs, and the expected profit and wage are higher, the more substitutable the tasks are for the agent.

**Proof** See the Appendix.

The intuition for part (a) is that if the productivities of the tasks are not already highly correlated, then the lower \( \rho \), the higher the value of the agent’s information because it is more likely that the agent should focus his effort on one task rather than both.

To understand part (b), recall that \( \phi \) measures how substitutable the two tasks are from the agent’s point of view. The higher \( \phi \), the less strongly the agent cares about what tasks he works on, and hence the more the agent allocates his effort according to his private information rather than his personal preferences. It is then optimal to put a larger weight on output-based compensation.\footnote{Thus, output-based pay is not a response to misaligned preferences between principal and agent (\( \phi < 1 \)) but is in fact more important the larger \( \phi \) is. Proposition 3 does rely on Assumption (a2') stated in the proof, though, which ceases to hold as \( \phi \) approaches 1. However, (a2') is only a technical condition to ensure an interior solution. If (a2') does not hold, the analysis and results are more complicated but very similar to those presented here.}
6. Implications and predictions

 Propositions 2 and 4 lead to several empirical predictions about optimal incentives and the choice of performance measures. They relate to characteristics of the agent’s job, the relationship between agent and principal, and properties of the firm or the firm’s environment.

 Most predictions relate to the knowledge parameter $k$, which is best interpreted as measuring the agent’s knowledge relative to that of the principal. To see why, suppose the principal and agent are symmetrically informed about the environment. Then the optimal incentive contract is entirely input based, irrespective of how well informed the two parties are. It is only when the agent has an information advantage over the principal that output-based pay may be optimal. Thus, Proposition 2 implies that the relative weight on output-based pay is positively related to the gap between agent and principal in knowledge pertaining to the agent’s job.

 Proposition 2 also implies that incentives are overall stronger the better informed the agent is, provided we indeed look at variations in the agent’s knowledge while holding the principal’s fixed. This additional constraint comes into play because the overall strength of incentives depends on absolute, not only relative, levels of knowledge; optimal incentives are stronger the better informed the principal and agent are.\(^\text{20}\)

 The discussion below focuses on predictions concerning the agent’s knowledge and related variables such as technological uncertainty and the correlation of effort productivities. The other parameters’ effects on the optimal contract are described in Propositions 2 and 4 but are not further discussed here.

 □ Knowledge gap. The results in Proposition 2 for $k$ imply that we should expect to see stronger incentives and a greater weight on output-based pay the better the agent’s specific knowledge about his job is relative to the principal’s knowledge. One way to test this prediction is to directly attempt to measure the gap in job-specific knowledge between agent and principal. This has been done with some success in accounting research using survey data. For instance, Abernethy, Bouwens, and van Lent (2004) and Bouwens and van Lent (2007) use a six-item scale developed by Dunk (1993) to measure the extent of information asymmetry between profit center managers and their superiors.\(^\text{21}\)

 This survey-based measure is strongly correlated with “harder” proxies of specific knowledge such as the manager’s experience (in years) in his current position, his age, and the ratio of industry experience between manager and superior (the difference in education backgrounds would be another possible proxy). Bouwens and van Lent (2007) find that the weight in managers’ compensation placed on aggregate accounting measures of division profit (=output), as opposed to disaggregated metrics or nonfinancial measures (=inputs), increases with measures of managers’ authority. An untested prediction is that even controlling for managers’ authority, the weight on output-based pay should increase with the extent of informational asymmetries. For other ways to measure specific knowledge directly, see Christie, Joye, and Watts (2003).

 Karuna (2006) finds that a CEO’s reputation is positively related to the relative weight on stock- versus earnings-based CEO compensation. As Karuna suggests (based on this article’s predictions), a possible interpretation is that CEOs considered to be particularly skilled (high $k$, or alternatively high $\bar{\theta}$) receive more output-based pay as an incentive to put their knowledge to use.

\(^{20}\) In contrast, the effects of an increase in the principal’s knowledge are ambiguous. It would lead to a decrease in the knowledge gap between principal and agent, but would also in general lead to the provision of stronger overall incentives to the agent. This ambiguity may explain the apparent contradiction between Proposition 2 and the result of Baiman, Larcker, and Rajan (1995) that “the compensation risk imposed on the business manager generally increases with the principal’s relative expertise.”

\(^{21}\) This involves literally including questions on the survey such as “Compared to your superior, who is more familiar with the input-out relationships inherent in the internal operations of your organizational unit?” and “Compared to your superior, who is more familiar technically with the work of your organizational unit?”

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Smith and Watts (1992) have linked both the level and the structure of executive compensation to a firm’s growth opportunities. They argue that the greater the growth options, the less shareholders are able to evaluate a CEO’s decisions, and hence the more they will want to tie compensation directly to firm value by placing a larger weight on stock-based pay. Although my model cannot shed light on Smith and Watts’s basic hypothesis, it supports their conclusion. Under Smith and Watts’s hypothesis, better growth options are associated with a larger value of $k$ (or $t$) because $k$ measures the knowledge gap between shareholders and a CEO. It then follows that firms with better growth options place a relatively larger weight on stock-based pay, consistent with the evidence of Smith and Watts (1992) and Gaver and Gaver (1993). Conversely, older firms and firms in more mature industries should be expected to place relatively less emphasis on stock-based pay due to a smaller knowledge gap between the board and CEO.

The agent’s knowledge advantage is also related to the degree of technological uncertainty. Although the parameters $k$ and $t$ do not play exactly the same role in the model, their roles in Propositions 2 and 4 are the same. This parallel suggests examining whether incentives are positively related to proxies of technological uncertainty. A candidate for such a proxy is the concept of “industry clockspeed” developed by Mendelson and Pillai (1998) as a quantitative measure “that gauges the velocity of change in the external business environment and sets the pace of . . . firms’ internal operations.” It is a composite of three variables: product life (the duration of the product life cycle), product “freshness,” measured by the share of total revenues due to products introduced over the previous 12 months, and the rate of change in input prices. Although all of these variables affect both technological and environmental risk, they are highly decision relevant, suggesting that clockspeed may be a suitable proxy for $t$. We then obtain the prediction that the strength of incentives and the weight on output measures should be positively related to clockspeed.

Job complexity. Several empirical researchers have studied the effects of job complexity on the level and structure of compensation. In the model, job complexity is captured both by $k$ and by $\rho$. First, the more complex the agent’s job is, the better the agent probably knows what actions are value maximizing relative to the principal, which corresponds to a higher value of $k$. Second, the smaller $\rho$, the more likely the $\theta_i$, and hence the efficient effort levels for each task, will be different. A job with smaller $\rho$ is thus more complex in the sense that the optimal allocation of total effort across tasks is more difficult to specify in advance. Both measures of job complexity lead to the same prediction that the weight on output-based incentives should vary positively with job complexity (see also Prendergast, 2002, on delegation as a function of job complexity).

In a recent paper that specifically tests predictions based on this article, Hwang, Erkens, and Evans (2006) proxy the importance of knowledge by a firm’s investment in advanced manufacturing technologies and information technology. Citing empirical work, they argue that such investments are often accompanied by hiring more skilled workers because their jobs are more complex. Hwang, Erkens, and Evans (2006) find that firms that make such investments are more likely to use output-based performance measures, as expected.

Propositions 2 and 4 also predict that the agent’s expected wage increases with job complexity, consistent with the evidence of Van Ophem, Hartog, and Vijverberg (1993) and Pekkarinen (2002). Van Ophem, Hartog, and Vijverberg argue that a more complex job requires greater effort or in other ways increases a worker’s disutility, for which a worker needs to be compensated. The model suggests a micro-foundation of this argument: as long as the contract is held fixed, the agent’s effort, wage, and utility do not vary with $\rho$ (although the wage does increase with $k$). But in a more complex job, it is optimal for the principal to shift incentives toward output-based pay, and this leads to higher effort, wage, and utility. Even if the principal could eliminate the agent’s rent

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22 Both measures differ from Kremer’s (1993), who assumes that tasks are complementary and defines complexity as the number of tasks. Here, the tasks are independent in the sense that the cross-partial derivatives of $E(Y)$ with respect to $a_1$ and $a_2$ are zero. It is likely, though, that in an extended model with $n$ tasks, $\beta_{a_i}$ increases with $n$. 

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as measured by his utility (as in a model with risk aversion and unlimited liability), higher effort and hence disutility would require a higher wage, consistent with the argument of Van Ophem, Hartog, and Vijverberg (1993).

Corporate governance. A substantial amount of recent research examines the connections between corporate governance and CEO compensation. A new view has become popular according to which CEO pay is determined in a process in which, as it were, the roles of board and CEO as principal and agent are reversed (see Bebchuk and Fried, 2004). A growing body of evidence documents that the “worse” companies are governed (using a variety of measures), the more money their CEOs make (see, e.g., Core, Holthausen, and Larcker, 1999; Bertrand and Mullainathan, 2001). This has been interpreted as evidence that CEOs are able to extract rents from shareholders when directors lack the ability or incentive to exert stronger control, or worse, when they believe to owe the CEO a favor in return for their appointment to the board. In support of this view, its proponents argue that if conventional theory were valid, we should not expect to see strong relations between the quality of governance and the level and structure of CEO pay.

Contrary to this view, once one recognizes that CEOs typically have specific knowledge about how to do their job, it is natural that both structure and level of CEO compensation would be related to characteristics of corporate governance. Specifically, Proposition 2 implies that the greater the knowledge gap between a CEO and the company’s board, the stronger the CEO’s incentives, the larger the weight on output (=stock)-based pay, and the higher the total compensation. The knowledge gap, in turn, depends on the characteristics of both principal and agent.

To illustrate, Core, Holthausen, and Larcker (1999) find that the level of CEO pay is positively related to the share of outsiders on the board. This is somewhat unexpected from a “managerial power” perspective because outsiders on the board are less likely to owe the CEO a favor, which is normally interpreted as leading to more effective governance. A different interpretation, however, is that outside directors also understand the firm less well, leading to a larger knowledge gap between board and CEO.²³

Taking the role of specific knowledge into account thus leads to connections between corporate governance and CEO compensation previously considered outside the domain of the theory of incentives. These connections include some that have been cited in support of an altogether different view of the process by which CEO pay is determined. More refined tests than previously employed are therefore necessary to distinguish the two contrasting views on how CEO pay is determined. More theory would be useful too: to some extent, “managerial power” may simply be an information rent resulting from specific knowledge. Incorporating knowledge into agency models thus also aids in bringing the two perspectives together.

7. Conclusion

In modern economies, information is dispersed both across market participants (see Hayek, 1945) and within firms. Managers, in particular, usually have unique knowledge about production and market conditions that in practice is too costly to communicate to others in the firm, and is hence “specific knowledge.” This knowledge is often the reason why agency relationships exist in the first place: “The reason shareholders entrust their money to self-interested CEOs is based on shareholder beliefs that CEOs have superior skill or information in making investment decisions” (Murphy, 1999a).

In standard models of incentive contracting, however, the agent has no private information on which to base his actions. His actions may be unobservable to the principal, but are always known in equilibrium. Incorporating specific knowledge (more precisely, postcontractual private

²³ This argument is supported by two broad trends: one toward better corporate governance, brought about, for instance, by greater outsider presence on boards (Hermalin, 2005; Murphy and Zabojnik, 2006); and a trend toward greater use of nonfinancial performance measures (Ittner and Larcker, 1998).
information) into the theory of incentives has been difficult because extensions of workhorse principal-agent models quickly prove to be analytically intractable.

This article studies the effects of specific knowledge on optimal incentives and performance evaluation in a model that leads to simple, closed-form solutions and intuitive comparative statics. The main formal result is that when an agent has specific knowledge about how his actions contribute to the principal’s objectives, the principal must provide incentives based on “output” measures correlated with those objectives rather than on measures correlated with the agent’s actions. This result is consistent with the evidence but violates the Informativeness Principle, according to which the objective of performance measurement should be to measure the agent’s effort as precisely as possible.

The formal results lead to a wide range of empirical predictions and other implications. Some of the predictions are supported by existing evidence, some suggest a reinterpretation of previous findings, and some are yet to be tested. Categorizing performance measures as inputs or output, linked by the agent’s specific knowledge, will hopefully also prove fruitful for the design of compensation plans in practice.

Appendix

• Proof of Proposition 1. The principal’s expected profit conditional on \((\theta, s)\) is

\[
\pi = Y(\theta, s) - w(\theta, s) = Y(\theta, s) - \beta_in a(s) - \beta_out \left[ \frac{e}{2} + (1 - e) Y(\theta, s) \right]
\]

\[
= [1 - \beta_out (1 - e)] Y(\theta, s) - \beta_out a(s) - \frac{\beta_out e}{2}.
\]

We want to compute the expected value of \((A1)\) over \((\theta, s)\). For \(Y\), we have

\[
Y(\theta, s) = a(s) \hat{\theta} = \frac{\beta_in a(\theta)}{d} + \frac{(1 - e) \beta_out \hat{\theta}}{d}.
\]

Putting everything together, the expected value of \((A2)\) is

\[
\frac{1}{d}[\beta_in + (1 - e)(1 + k^2 \tau^2) \beta_out].
\]

Moreover, using \((4)\), the expected value of \(a(s)\) is simply \([\beta_in + (1 - e) \beta_out \hat{\theta}] / d\). Substitute this expression and \((A3)\) into \((A1)\) to obtain the principal’s expected profit:

\[
E(\tau) = \frac{1}{d} \left[ 1 - \beta_out (1 - e) [\beta_in + (1 - e) \beta_out (1 + k^2 \tau^2) \hat{\theta}] - \frac{\beta_in \beta_out (1 - e) \hat{\theta} - \frac{\beta_out e}{2}}{2}. \right.
\]

Differentiating \((A4)\) with respect to \(\beta_in\) and \(\beta_out\) leads to the first-order conditions

\[
[1 - 2(1 - e) \beta_out] \hat{\theta} - 2 \beta_in = 0 \quad \text{and} \quad \left(1 - 2(1 - e) \beta_out \right) \hat{\theta}^2 - \frac{\beta_in \beta_out (1 - e) \hat{\theta} - \frac{\beta_out e}{2}}{2}.
\]

The solution of \((A5)\) and \((A6)\) for \(\beta_in\) and \(\beta_out\) is stated in the proposition. It is straightforward to establish that \((A4)\) is strictly concave in \(\beta_in\) and \(\beta_out\) and so the solution of \((A5)\) and \((A6)\) is indeed a maximum.

It is straightforward to verify that \(\beta_out\) in \((10)\) is positive if and only if Condition \((a1)\) holds. Moreover, we need to make sure \(\theta a\) does not exceed 1. It attains its largest value when \(\tau = s = 1\). Using \((4)\) and \(\hat{\theta} = (1 + kts) \theta\), we obtain

\[
Y(1, 1) = \frac{1}{d} \left[ \beta_in + (1 - e) \beta_out (1 + k \theta^2) \right] \hat{\theta} = \frac{(1 + t) [2(1 - e) k t (1 + k \theta^2 - d \epsilon)]}{4d(1 - e) k t}.
\]

Subtracting the numerator in \((A7)\) from the denominator leads to the left-hand side of Condition \((a2)\). Thus, under \((a2)\), \(\theta a\) does not exceed 1.

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To obtain the expected value of effort, plug the optimal $\beta_{in}$ and $\beta_{out}$ into expected value of effort $E[a(s)] = [\beta_{in} + (1 - e)\beta_{out}]d$ stated above. The result is $E(a) = \hat{\theta}/(2d)$. By comparison, the expected total surplus between principal and agent, $E[Y - d(a)] = \bar{\theta}a - d/2a^2$, is maximized at $a^{\ast}\beta = \hat{\theta}/d$, which means the \textit{ex ante} expected value is $E(a') = \hat{\theta}/d$.

The principal's expected profit is obtained by substituting the optimal contract parameters from the proposition into (A4), which leads to (6). The agent's wage is $w = \beta_{in}a + \beta_{out}y$, and so the expected wage is

$$E(w) = \beta_{in}E(a) + \beta_{out}\left(\frac{e}{2} + (1 - e)E(Y)\right).$$

Using $E(a) = [\beta_{in} + (1 - e)\beta_{out}]d$ (see above) and (A3), and then substituting the optimal contract parameters (5) for $\beta_{in}$ and $\beta_{out}$, leads to (7).

\textbf{Q.E.D.}

\textbf{Proof of Proposition 2} Parts (a) and (b): for $k, \theta, t, \rho$, and $d$, the results follow by inspection of the expressions in (5). Also by inspection, $\beta_{in}^{\ast}$ is increasing in $e$. The derivative of $\beta_{out}^{\ast}$ with respect to $e$ is negative if and only if

$$2(1 - e)k^2i^2\hat{\theta}^2 - d(1 + e) > 0. \quad (A8)$$

Next, use (8) and (A7) to obtain the \textit{ex ante} expected value of $y$ as function of $\beta_{in}$ and $\beta_{out}$:

$$E(y) = \frac{e}{2} + \frac{(1 - e)\hat{\rho}}{d}[\beta_{in} + (1 - e)(1 + k^2i^2)\beta_{out}]^2. \quad (A9)$$

The derivative of $E(y)$, evaluated at $\beta_{in}^{\ast}$ and $\beta_{out}^{\ast}$, has the same sign as

$$d(e + 2k^2i^2) - 4(1 - e)k^2i^2(1 + k^2i^2)\hat{\theta}^2. \quad (A10)$$

The difference $2(1 + k^2i^2$) times (A8) minus (A10) is $d(2 + e + 2ek^2i^2) > 0$, which means that $\beta_{out}^{\ast}$ decreases with $e$ whenever $E(y)$ increases, proving part (a) for $e$.

Part (c) is straightforward to establish by differentiating (6) and (7) with respect to the various parameters. The signs of the derivatives of $E(w)$ are always obvious. The signs of the derivatives of $E(\tau)$ are unambiguous too, given Assumption (a1).

\textbf{Q.E.D.}

\textbf{Proof of Proposition 3} As will be shown, the conditions necessary for the existence of an interior solution are the following three:

\begin{align*}
(a1') \quad 2(1 - e)k^2i^2\eta^2 &> (1 - \phi)de. \\
(a2') \quad (1 - \phi^2)(1 - \rho)de + 2(1 - e)\eta k\hat{\rho}^2(1 - \phi)(1 - k^2\rho) - (1 + \phi)(1 - \rho)kt &> 0. \\
(a3') \quad 2(1 - e)(1 + k^2\rho)\eta k2d - (1 + t)\phi^2 - (1 + t)(1 + \rho)(2(1 - e)\eta k^2i^2\hat{\theta}^2 - de(1 - \phi)) &> 0.
\end{align*}

In stage 4 of the game, the agent chooses his effort $a$ as a function of his beliefs $\hat{\theta}$ about $\theta$. Assuming an interior solution for all endogenous variables, the agent’s expected utility is

$$\beta_{in}(a_1 + a_2) + \beta_{out}[e/2 + (1 - e)(\hat{\theta}(a_1 + \hat{\theta}a_1)) - \frac{d}{1 + \phi}(a_1^2 + a_2^2 + 2\phi_a1a_2)]. \quad (A11)$$

This expression is strictly concave in $a$, and maximization with respect to $a$ leads to

$$a_i^\ast(\hat{\theta}) = \frac{\hat{\beta}_{in}}{2d} + \frac{(1 - e)(\hat{\theta}(a_1 - \phi\hat{\theta}))\beta_{out}}{2d(1 - \phi)}. \quad (A12)$$

for $i = 1, 2; j \neq i$, which is an affine function of $\hat{\theta}$.

Let us next determine $\hat{\theta}$. For $\tau \in \{-1, 1\}$, we have $\tau_1\tau_2 = 1$ if $\tau_1 = \tau_2$ and $\tau_1\tau_2 = -1$ otherwise. Because $Pr(\tau_1 = \tau_2) = (1 + \rho)/2$, it follows that for $\tau \in \{-1, 1\}^2$, we have $Pr(\tau) = (1 + \rho\tau_1\tau_2)/4$. Moreover, because $Pr(s_i = \tau_i) = (1 + k)/2$ and the conditional distributions $s_i | \tau_i$ are independent, it follows that for any $(\tau, s) \in \{-1, 1\}^4$, the probability of $s$ conditional on $\tau$ is given by $Pr(s | \tau) = (1 + ks_i\tau_i)(1 + ks_i\tau_j)/4$. The unconditional probability of $s \in \{-1, 1\}^2$ is then given by $Pr(s) = \sum s \in \{-1, 1\}^2_pr(s | \tau)Pr(\tau)$, which simplifies to $(1 + k^2\rho s_1 s_2)/4$. The expected value of $s$ conditional on $s$ is therefore given by

$$E(\tau | s) = \sum \tau \frac{Pr(s | \tau)Pr(\tau)}{Pr(s)},$$

which reduces to

$$E(\tau_i | s) = \frac{k(s_i + \rho s_i)}{1 + k^2\rho s_i s_j}$$

for $i = 1, 2$ and $j \neq i$. We therefore have

$$\hat{\theta}(s) = \left[1 + \frac{k(s_i + \rho s_i)}{1 + k^2\rho s_i s_j}\right]\hat{\theta} \quad \text{for} \quad i = 1, 2 \quad \text{and} \quad j \neq i. \quad (A13)$$
In particular, for \( k = 0 \) we have \( \hat{\theta} = \bar{\theta} \), whereas for \( k = 1 \), \( \hat{\theta} = \theta \), irrespective of \( \rho \) and \( s \), which follows because \( s_i \in \{−1, 1\} \). As in the one-task model, what remains is to substitute (A12) and (A13) into the principal’s profit function and take expectations over \( \tau \) and \( s \). The principal’s expected profit conditional on \( \theta, s \) is

\[
\pi = Y(\theta, s) - w(\theta, s)
\]

\[
= Y(\theta, s) - \beta_{in}(a_1(s) + a_2(s)) - \beta_{out} \left[ \frac{e}{2} + (1-e)Y(\theta, s) \right]
\]

\[
= [1 - \beta_{out}(1-e)]Y(\theta, s) - \beta_{in}(a_1(s) + a_2(s)) - \frac{\beta_{out} e}{2}.
\]

To obtain the expected value of (A14) over \( \theta, s \), we need to evaluate the expected values of \( a_1(s) + a_2(s) \) and \( Y(\theta, s) \).

First, notice from (A12) that

\[
a_1 + a_2 = \frac{1}{2d} [2\beta_{in} + (1-e)[\hat{\theta}_1(s) + \hat{\theta}_2(s)]\beta_{out}],
\]

where the expected value of \( \hat{\theta}_1(s) + \hat{\theta}_2(s) \) over \( s \) is \( 2\bar{\theta} \).

Hence, the expected value of \( a_1 + a_2 \) in (A14) over \( s \) is given by

\[
\frac{\beta_{in} + \beta_{out}(1-e)}{d} \hat{\theta}.
\]

Next, we have

\[
Y(\theta, s) = a_1'(s)\theta_1 + a_2'(s)\theta_2 = \frac{\beta_{in}}{2d}(\theta_1 + \theta_2) + \frac{(1-e)\beta_{out}}{2d(1-\phi)} \left[ \theta_1(\theta_1 - \phi\hat{\theta}_n) + \theta_2(\theta_2 - \phi\hat{\theta}_n) \right]
\]

(3.2.2) (omitted). The expected value of \( \theta_1 + \theta_2 \) in the first term is \( 2\bar{\theta} \).

Obtaining the expected value of the term in \( \{\} \) brackets requires evaluating the term for each of the 16 permutations of \( (\theta_1, \theta_2, s_1, s_2) \) and weighting it with the corresponding probability of the permutation, given by \( (1 + k s_1, t_1)(1 + k s_2, t_2)(1 + \rho, t_1, t_2)/16 \). The computation is complex but the result simple: it is \( 2(1 - \phi + k^2 r^2)\eta \bar{\theta}^2 \), with \( \eta \) as defined in (9). Thus, the expected value of (A16) is

\[
\frac{\partial \beta_{in}}{d} + \frac{(1-e)\beta_{out}\bar{\theta}^2}{d(1-\phi)} (1 - \phi + k^2 r^2 \eta).
\]

Substitute (A15) and (A17) into (A14) to obtain the principal’s expected profit:

\[
E(\pi) = [1 - \beta_{out}(1-e)] \left[ \frac{\partial \beta_{in}}{d} + \frac{(1-e)\beta_{out}\bar{\theta}^2}{d(1-\phi)} (1 - \phi + k^2 r^2 \eta) \right] - \beta_{in} - \beta_{out}(1-e)\bar{\theta} - \frac{\beta_{out} e}{2}.
\]

Differentiating (A18) with respect to \( \beta_{in} \) and \( \beta_{out} \) leads to the first-order conditions

\[
\frac{1 - 2(1-e)\beta_{out}}{d(1-\phi)} \bar{\theta} - 2\beta_{in} = 0 \quad \text{and} \quad \frac{-e}{2} + \frac{(1-e)\bar{\theta}}{d(1-\phi)} \left[ 1 - 2(1-e)\beta_{out}(1 - \phi + k^2 r^2 \eta)\bar{\theta} - 2(1 - \phi)\beta_{in} \right] = 0.
\]

The solution of (A19) and (A20) for \( \beta_{in} \) and \( \beta_{out} \) is stated in the proposition. Because

\[
\frac{\partial^2 E(\pi)}{\partial \beta_{in}^2} - \frac{\partial^2 E(\pi)}{\partial \beta_{out}^2} - \frac{\partial^2 E(\pi)}{\partial \beta_{in} \partial \beta_{out}} = \frac{2(1-e)(1 - \phi + k^2 r^2 \eta)\bar{\theta}^2}{d(1-\phi)} < 0 \quad \text{and} \quad \frac{\partial^2 E(\pi)}{\partial \beta_{in}^2} - \frac{\partial^2 E(\pi)}{\partial \beta_{out}^2} = \frac{(4 - e)\theta \eta k^2 r^2 \bar{\theta}^2}{d^2(1-\phi)} > 0,
\]

\( E(\pi) \) is strictly concave in \( \beta_{in} \) and \( \beta_{out} \) and so the solution of (A19) and (A20) is indeed a maximum. What remains to be shown is that under (a1’)-(a3’), the interior solution obtained here is indeed valid. Three conditions must be satisfied:

(i) The expression for \( \beta_{in}^* \) in (10) must be positive; otherwise, we obtain a corner solution with \( \beta_{out}^* = 0 \). It is straightforward to verify that this condition is equivalent to (a1’).

(ii) The agent’s effort must be positive for each realization of \( s \) for (A12) to be valid. There are two candidates for the lowest value of \( a_i(s) \), namely \( a_i(-1, -1) \) and \( a_i(-1, -1) \). Using (A12) and (A13), the sign of the difference \( a_i(-1, -1) - a_i(-1, -1) \) can be computed as

\[
\phi(1 - k^2\rho^2) - \rho(1 - k^2).
\]

(A21)

If (A21) is negative, the smallest value of \( a_i \) is given by

\[
a_i(-1, -1) = \frac{(1 + k^2 \rho)\beta_{in} + (1 - e)\beta_{out}\bar{\theta}[(1 - k)(1 - \rho) + k(1 - \tau)(1 + \rho)]}{2d(1 + k^2 \rho)}.
\]

which is always positive. If (A21) is positive, the smallest value of \( a_i \) is given by \( a_i(-1, -1) \). Using (A12) and substituting for \( \bar{\theta} \) from (A13) and for \( \beta_{in} \) and \( \beta_{out} \) from (10), one can verify that the condition for \( a_i(-1, -1) \) to be positive is given by (a2’).
(iii) Finally, \( \theta, a_1, \theta_2, a_2 \) must not exceed 1. The largest value of \( \theta, a_1, \theta_2, a_2 \) is attained when \( \tau = \Phi, \) and using (A12) and (A13) leads to

\[
Y((1, 1), (1, 1)) = \frac{(1 + t)\tilde{\theta}}{d} \left[ \beta_{in} + (1 - e) \frac{(1 + k^2 \rho + (1 + \rho)k\tilde{\theta})\beta_{out}}{1 + k^2 \rho} \right],
\]

which is less than 1 as long as

\[
d(1 + k^2 \rho) > (1 + t)\tilde{\theta}[(1 + k^2 \rho)\beta_{in} + (1 - e)(1 + k^2 \rho + (1 + \rho)k\tilde{\theta})\beta_{out}].
\]  

(A22)

Substituting for \( \beta_{in} \) and \( \beta_{out} \) in (A22) from (10), and using (9), leads to condition (a3').

An example proves that parameters satisfying (a1')–(a3') exist: take \( \tilde{\theta} = 1, e = .1, k = .5, d = 1, \rho = 0, \) and \( \phi = .5, \) in which case \( \eta = 1. \)

Proof of Proposition 4 Because \( \eta \) depends only on \( k, \rho, \) and \( \phi, \beta_{\ast in} \) is obviously increasing in \( \tilde{\theta} \) and \( t, \) and decreasing in \( d; \) the opposite holds for \( \beta_{\ast out} \). Likewise, \( \beta_{\ast in} \) is obviously increasing in \( e. \) The effect of \( e \) on \( \beta_{\ast out} \) is the same as stated in Proposition 2, and the steps to prove it are the same too.

Next, \( \beta_{\ast out} \) is increasing in \( k, \) and \( \beta_{\ast in} \) is decreasing, if and only if \( k^2 \eta \) is increasing in \( k. \) That is the case, because substituting from (9) one can compute

\[
\frac{\partial (k^2 \eta)}{\partial k} = \frac{2k[(1 - \rho)(k^2 \rho)^2 + 2(1 - k^2)(k^2 \rho^2) - \rho(1 - k^2)]}{(1 - k^2)(k^2 \rho)^2} > 0.
\]

Next, \( \beta_{\ast out} \) is decreasing in \( \rho, \) and \( \beta_{\ast in} \) is increasing, if and only if \( \eta \) is decreasing in \( \rho. \) The derivative of \( \eta \) with respect to \( \rho \) is

\[
-2(1 - k^2)^2 + \phi \rho k(3 - 2k^2 + k^4(1 - \rho^2)),
\]

which is always negative. This establishes the existence of a critical value \( \bar{\rho} \in (0, 1) \) such that (11) holds for all \( \rho \leq \bar{\rho}. \)

Next, \( \beta_{\ast out} \) is increasing in \( \phi, \) and \( \beta_{\ast in} \) is decreasing, if and only if \( \eta/(1 - \phi) \) is increasing in \( \phi. \) This is the case, because using (9) the derivative of \( \eta/(1 - \phi) \) with respect to \( \phi \) is

\[
(1 - \rho^2 - k^2\rho^2 - \rho(1 - k^2)).
\]

The principal's expected profit is obtained by substituting (10) into (A18), which leads to

\[
E(\pi) = \frac{4(1 - e)^2 \eta k^2 \tilde{\theta}^2 (1 - \Phi + \eta k^2 \tilde{\theta}) \tilde{\theta}^3 - 4de(1 - e)(1 - \Phi)\eta k^2 \tilde{\theta}^2 \tilde{\theta}^2 + d^2 e^2 (1 - \Phi)^2}{16d(1 - e)^2(1 - \Phi)\eta k^2 \tilde{\theta}^2 \tilde{\theta}^2}.
\]  

(A23)

Like in Proposition 2, most derivatives of \( E(\pi) \) can be computed and signed in a straightforward manner, using Assumption (a1'). For \( \rho, \) one can first establish that (A23) is increasing in \( \eta, \) and above we established that \( \eta \) is decreasing in \( \rho \) if and only (11) holds. For \( \phi, \) it is easiest to differentiate (A18) instead, observing that because of the envelope theorem, we can use the partial derivative instead of differentiating with respect to \( \beta_{\ast in} \) and \( \beta_{\ast out} \) and observing that \( \eta \) is a function of \( \rho, \) inspection of (A18) reveals that \( E(\pi) \) is increasing in \( \phi \) if and only if \( \eta/(1 - \phi) \) is increasing in \( \phi, \) which we established above.

The agent's expected wage is given by

\[
E(w) = \frac{4(1 - e)^2 \eta k^2 \tilde{\theta}^2 (1 - \Phi + \eta k^2 \tilde{\theta}) \tilde{\theta}^3 - d^2 e^2 (1 - \Phi)^2}{16d(1 - \Phi)(1 - e)^2 \eta k^2 \tilde{\theta}^2 \tilde{\theta}^2}.
\]  

(A24)

All results for \( E(w) \) follow in straightforward fashion from differentiation.

Q.E.D.

References


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