# **Relative Performance Evaluation**

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## Model I

Relative Performance Evaluations are widely used when individual performances can be observed:

- At School: In grading, ranking etc.
- At Work: In promotions, hiring and firing, etc.
- In Sports: In declaring winner, runners-up etc.

### Question

- Is relative performance evaluation efficient?
- Should the wage/reward be based only on the absolute value of the output, or also on the relative ranking of performances?

Consider:

One Principal and Two agents and Two outputs

## Model II

- Two agents produce Two (possibly different) individually observable outputs
- Principal is Risk-neutral but agents are Risk-averse with CARA preferences

The production technology:  $Q = q_1 + q_2$ , where

$$q_1(e_1, \epsilon_1, \epsilon_2) = e_1 + \epsilon_1 + \alpha \epsilon_2$$
  
$$q_2(e_2, \epsilon_1, \epsilon_2) = e_2 + \epsilon_2 + \alpha \epsilon_1$$

where  $\epsilon_1$  and  $\epsilon_2$  are *iid* with  $\epsilon_i \sim N(0, \sigma^2)$ . Three cases:

- $\alpha = 0$ : Technologically independent outputs
- $\alpha > 0$ : Positively correlated outputs
- $\alpha < 0$ : Negatively correlated outputs

## Model III

- Principal is risk-neutral.  $V(q_1, q_2, w) = E[q_1 + q_2 w_1 w_2]$
- Agents are risk-averse.  $u_i(w_i, e) = -e^{-r_i(w_i \psi_i(e))}$ ,  $r_i > 0$ , where

• 
$$r_i = -\frac{u_i''}{u_i'} > 0$$
, i.e., CARA, and

- $\psi_i(e) = \frac{1}{2}c_ie^2$  is the (money) cost of effort *e* by agent *i*.
- e is not contractible but  $q_i$ s are.

For simplicity assume:

• 
$$r_1 = r_2 = r$$
, and  $c_1 = c_2 = c$ , as a result,  $\psi_1(.) = \psi_2(.) = \psi(.) = \frac{1}{2}ce^2$ 

• Linear Contracts:

$$w_1(q_1, q_2) = t_1 + s_1 q_1 + \tilde{s}_1 q_2$$
  
$$w_2(q_1, q_2) = t_2 + s_2 q_2 + \tilde{s}_2 q_1$$

## Model IV

- $\tilde{s}_1 = 0$  and  $\tilde{s}_2 = 0$  will imply no relative performance evaluation.
- When is it optimum to have  $\tilde{s}_1 \neq 0$  and  $\tilde{s}_2 \neq 0$ ?

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## Model V

Second Best: The principal will solve

$$\max_{s_i,\tilde{s}_i,t_i} E(\sum q_i - \sum w_i)$$

However, since the agents are assumed to be identical, for each agent the principal solves

$$\max_{s_i,\tilde{s}_i,t_i} E(q_i - w_i)$$

say

$$\max_{s_1,\tilde{s}_1,t_1} E(q_1-w_1)$$

s.t.

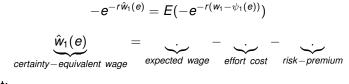
$$E(u_{1}(w_{1}, e_{1})) = E(-e^{-r(w_{1}-\psi(e_{1}))}) \geq -e^{-r(\bar{w})} = u(\bar{w})$$
(IR)  
$$e_{1} = \arg\max_{e} E(-e^{-r(w_{1}-\psi(e))})$$
(IC)

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## Model VI

e1 is the effort chosen by first agent. Let's define



Note that:

$$w_1(q_1, q_2) = t_1 + s_1 q_1 + \tilde{s}_1 q_2$$
  
=  $t_1 + s_1(e_1 + \epsilon_1 + \alpha \epsilon_2) + \tilde{s}_1(e_2 + \epsilon_2 + \alpha \epsilon_1)$   
=  $t_1 + s_1 e_1 + \tilde{s}_1 e_2 + s_1(\epsilon_1 + \alpha \epsilon_2) + \tilde{s}_1(\epsilon_2 + \alpha \epsilon_1)$ 

Therefore,

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## Model VII

$$\begin{aligned} & \operatorname{Var}[w_1(q_1, q_2)] &= \operatorname{Var}[s_1(\epsilon_1 + \alpha \epsilon_2) + \tilde{s}_1(\epsilon_2 + \alpha \epsilon_1)], i.e., \\ &= \operatorname{Var}[(s_1 + \alpha \tilde{s}_1)\epsilon_1 + (\tilde{s}_1 + \alpha s_1)\epsilon_2], i.e., \\ &= \sigma^2[(s_1 + \alpha \tilde{s}_1)^2 + (\tilde{s}_1 + \alpha s_1)^2]. \end{aligned}$$

The two agents will choose efforts independently in a N.E.

For given  $e_2$  opted by the second agent, the certainty equivalent payoff of the first agent is a function of his effort level  $e_1$  and is given by

$$\hat{w}_1(e) = E(w_1(q_1, q_2)) - \frac{1}{2}ce^2 - \frac{r\sigma^2}{2}[(s_1 + \alpha \tilde{s}_1)^2 + (\tilde{s}_1 + \alpha s_1)^2], i.e.,$$

in view of  $w_1(q_1, q_2) = t_1 + s_1q_1 + \tilde{s}_1q_2$ ;  $q_1(e_1, \epsilon_1, \epsilon_2) = e_1 + \epsilon_1 + \alpha\epsilon_2$ , and  $q_2(e_2, \epsilon_1, \epsilon_2) = e_2 + \epsilon_2 + \alpha\epsilon_1$ , we have

$$E(w_1(q_1, q_2)) = t_1 + s_1 e + \tilde{s}_1 e_2.$$

# Model VIII

Therefore,

$$\hat{w}_{1}(e) = t_{1} + s_{1}e + \tilde{s}_{1}e_{2} - \frac{1}{2}ce_{1}^{2} - \frac{r\sigma^{2}}{2}[(s_{1} + \alpha\tilde{s}_{1})^{2} + (\tilde{s}_{1} + \alpha s_{1})^{2}]$$
(1)

So, given e2, the agent 1 will solve

$$\max_{e} \{t_1 + s_1 e + \tilde{s}_1 e_2 - \frac{1}{2} c e_1^2 - \frac{r \sigma^2}{2} [(s_1 + \alpha \tilde{s}_1)^2 + (\tilde{s}_1 + \alpha s_1)^2]\}$$
(2)

That is,  $e_1^{SB}$  solves the following foc

$$e_1^{SB} = \frac{s_1}{c} \tag{3}$$

Now from (1) and (3), we get

$$\hat{w}_{1}(e_{1}^{SB}) = t_{1} + \frac{s_{1}^{2}}{2c} + \frac{\tilde{s}_{1}s_{2}}{c} - \frac{r\sigma^{2}}{2}[(s_{1} + \alpha\tilde{s}_{1})^{2} + (\tilde{s}_{1} + \alpha s_{1})^{2}]$$
(4)

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## Model IX

Now, in view of  $e_1^{SB} = \frac{s_1}{c}$ , the P's problem can be written as

$$\max_{t_1,\tilde{s}_1,s_1} \{ \frac{s_1}{c} - (t_1 + \frac{s_1^2}{c} + \frac{\tilde{s}_1 s_2}{c}) \}$$

s.t.

$$\hat{w}_{1} = t_{1} + \frac{s_{1}^{2}}{2c} + \frac{\tilde{s}_{1}s_{2}}{c} - \frac{r\sigma^{2}}{2}[(s_{1} + \alpha\tilde{s}_{1})^{2} + (\tilde{s}_{1} + \alpha s_{1})^{2}] = \bar{w}_{1}$$
(5)

Using the value of  $t_1$  from (5) and ignoring  $\bar{w}_1$ , the P's problem can be rewritten as

$$\max_{\tilde{s}_1,s_1} \{ \frac{s_1}{c} - \frac{s_1^2}{2c} - \frac{r\sigma^2}{2} [(s_1 + \alpha \tilde{s}_1)^2 + (\tilde{s}_1 + \alpha s_1)^2] \}$$

**Remark:** Note: For given  $s_1$ , optimizing the above w.r.t.  $\tilde{s}_1$  is equivalent to solving

$$\min_{\tilde{s}_1} \{ \frac{r\sigma^2}{2} [(s_1 + \alpha \tilde{s}_1)^2 + (\tilde{s}_1 + \alpha s_1)^2] \}$$

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## Model X

So, for given  $s_1$ ,  $\tilde{s}_1^{SB}$  solves the following the following foc

$$\tilde{s}_1^{SB} = -(\frac{2\alpha}{1+\alpha^2})s_1 \tag{6}$$

In view of (6), the P's problem reduces to

$$\max_{s_1} \{ \frac{s_1}{c} - \frac{s_1^2}{2c} - \frac{r\sigma^2}{2} s_1^2 \frac{(1-\alpha^2)^2}{(1+\alpha^2)} \}$$

So, the  $s_1^{SB}$  solves the following foc

$$s_1^{SB} = \frac{1 + \alpha^2}{1 + \alpha^2 + rc\sigma^2(1 - \alpha^2)^2}$$
(7)

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## Model XI

### Remark

- From (6) note that α = 0 ⇒ s<sub>1</sub><sup>SB</sup> = 0 and α = 0 ⇒ s<sub>1</sub><sup>SB</sup> = 1/(1+rcσ<sup>2</sup>). That is, if the outputs are technologically independent than relative performance evaluation is not optimum. Why?
- α > 0 ⇒ š<sub>1</sub><sup>SB</sup> < 0, i.e., an agent is penalized[rewarded] when the other individual's performance is higher[lower].</li>
- However, α < 0 ⇒ š<sub>1</sub><sup>SB</sup> > 0. In this case, an agent is compensated[penalized] when the other agent's performance is higher [lower].

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## Model XII

#### Remark

- From (6),  $(\alpha \rightarrow 1) \Rightarrow [\tilde{s}_1^{SB} = -s_1^{SB}]$  and from (7),  $(\alpha \rightarrow 1) \Rightarrow [s_1^{SB} = 1]$ .
- When α = 1, there is a common shock affects the two performances. In this case, the relative performance evaluation allows filtering out of the common shock.
- Therefore, the FB can be implemented even with risk-averse agents.

#### Question

Suppose  $\alpha = 1$ . Can the agents collude and choose e = 0 each?

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