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Max-Frederik Neubert/ Barbara Schöndube-Pirchegger

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Verantwortlich für diese Ausgabe:
M. F. Neubert, B. Schöndube-Pirchegger
Otto-von-Guericke-Universität Magdeburg
Fakultät für Wirtschaftswissenschaft
Postfach 4120
39016 Magdeburg
Germany

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Max-Frederik Neubert

Otto-von-Guericke Universität Magdeburg

Universitätsplatz 2, 39106 Magdeburg, Germany

(corresponding author)

Barbara Schöndube-Pirchegger

Chair in Accounting and Control

Otto-von-Guericke Universität Magdeburg

Universitätsplatz 2, 39106 Magdeburg, Germany

Phone: 0049/391/6758728

E-Mail: barbara.schoendube@ovgu.de

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Abstract

This paper investigates incentive effects from subjective performance evaluation (SPE) in an agency setting. An employee (agent) is evaluated by his superior (principal) via a subjective, potentially biased, performance report. We assume that this subjectiveness in evaluation affects the utility of both players, causing costs from biasing the report to the principal and benefits (costs) from over- (under-) evaluation to the agent.

If the superior chooses the reporting bias sequentially optimal, we find that benefits from subjective, as opposed to objective performance measurement, do not outweigh its costs. If, in contrast, the supervisor is able to commit to an ex ante optimal bias choice, SPE can be beneficial if the agent's preference for over-evaluation is sufficiently strong. While a centrality bias arises independent from the supervisor's ability to commit, a leniency bias results only along with an ex ante optimal bias.

Keywords

agency, subjective performance evaluation, behavioral accounting, accuracy, leniency, centrality

JEL-Classification: C72, D82, M40, M52

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None.

1 Introduction

Incentive problems are omnipresent in the corporate world and a broad literature investigates how performance-based compensation contracts can help mitigating these problems. Most of this literature assumes that performance evaluation can be based on objective measures. Unfortunately, objective performance measures are unavailable or inappropriate for many jobs. They either fail to reflect important dimensions of an employee's performance or are mainly sensitive to factors beyond the employee's control or both (Baker et al. 1994; Prendergast 1999; Sebald and Walzl 2015). Consequently, firms extensively revert to subjective performance assessments executed by the employee's superiors or supervisors. As opposed to an objective performance evaluation, subjective measurement implies that the person in charge of the evaluation enjoys discretionary power over the result. As the evaluator uses his/her own private impressions and observations of the employee's performance, he/she also gets the chance to distort the report. This option to bias adds an additional layer to the contracting problem as it addresses specific preferences of both, the employee and the supervisor, and thus affects their utility and incentives.

We consider a one-shot principal-agent model in what follows. A risk neutral supervisor (principal, she) hires a risk averse employee (agent, he) to contribute to some project. The agent's effort is private information and no objective performance measure is available to measure his contribution to project success. The principal writes a possibly biased report on the agent's performance at the end of the game that enters his compensation contract. The agent is aware of the potential bias in the report.

In order to address specifics of subjective performance evaluation (SPE), we build on findings from previous literature and integrate them into the respective utility functions of principal and agent. In particular, we assume that the supervisor has an incentive to downward bias the evaluation report in order to save on payment (Bull 1987; Baker et al. 1994; Baiman and Rajan 1995; Prendergast 1999; Bol 2008; MacLeod 2003). Doing so, however, is probably costly as effort is required to put together a biased but still convincing report. In addition, several authors argue that a disutility is likely to arise from violating a general preference for accurate ratings and/or truth-telling (Gneezy 2005; Golman and Bhatia 2012; Grund and Przemeck 2012; Maas et al. 2012; Abeler et al. 2019). The employee, in contrast, likely anticipates the supervisor's behavior. He/she forms personal expectations regarding an appropriate evaluation and possibly suffers a psychological gain or loss when the actual evaluation differs from the expected one (Daido and Murooka 2016; Köszegi and Rabin 2006, 2007).

We contrast the results from this model to a benchmark setting in which an objective measure is available. Naturally, an option to distort the measure is absent in the benchmark and so are any SPE-related preferences. We find that agency costs with subjective performance evaluation turn out to be larger than in the benchmark setting.

This result is partially driven by the fact that the principal decides about her bias late in the game. Picking the bias sequentially optimal, she ignores its effect on the agent's effort incentives and his risk exposure. A downward distortion of the report turns out to be optimal. It reduces compensation costs, but also violates the principal's truth-telling preference and results in effort costs for biasing the report. Moreover, as the principal anticipates her own biasing behavior, she also picks a downward distorted incentive rate, which causes further distortions from the optimal risk and incentive trade-off. With regard to the agent, systematic under-evaluation causes a psychological loss. In addition, the agent anticipates that, with an option to bias, additional effort does neither directly result in an increase of the performance measure nor in additional compensation. As a consequence, incentive provision becomes harder and induced effort is lower in equilibrium.

Having identified that part of the additional agency costs with SPE arises from the sequentially optimal choice of bias, we additionally consider an adapted setting. We introduce a simple mechanism, that allows the principal to commit herself to an ex ante optimal biasing behavior. We find that in this adapted setting, the above mentioned incentive to downward distort the report is absent. Rather, a systematic over-evaluation of the agent arises in equilibrium. Accordingly, we find that with SPE specific effects in place, a non-zero bias is optimal, also from an ex ante perspective. Moreover, it turns out that SPE is no longer dominated by objective performance evaluation.

Given these results, our paper helps to explain two types of biases commonly observed in empirical studies: the leniency bias and the centrality bias (see Baker et al. 1994; Flabbi and Ichino 2001; Gibbs and Hendricks 2004; Dohmen et al. 2004; Frederiksen 2010; Frederiksen and Takats 2011; Bol 2011; Bol and Smith 2011; Breuer et al. 2013; Bol et al. 2016). While the former indicates that supervisors tend to bias employee ratings upwards, the latter depicts that ratings are compressed around some norm and do not truly distinguish good from bad performances (Prendergast 1999).

As performance measure volatility decreases in both SPE-settings, a centrality bias arises endogenously. A leniency bias, in contrast, is absent within our first SPE-setting. Allowing for an ex ante optimal bias, however, a lenient evaluation becomes optimal for the principal.

Our paper contributes to a large stream of literature that empirically and/or analytically investigates agency problems arising with subjective performance evaluations. Part of the analytical literature considers settings, in which the evaluator does not bear any financial consequences from the outcome of the evaluation (Prendergast 1993; Prendergast and Topel 1996; Grund and Przemeck 2012; Kamphorst and Swank 2012; Golman and Bhatia 2012). In this literature, the superior does not necessarily intend to enhance firm value, but rather considers his/her own personal costs and benefits from biasing an evaluation. Some of the studies even assume that the superior somewhat embraces the utility function of the subordinate. Leniency- and centrality bias arise almost naturally in this literature.

Closer to our paper are those studies in which the principal is the residual claimant, in particular MacLeod (2003), Suvorov and van de Ven (2009), Zábojník (2014), and Sebald and Walzl (2015). These papers also consider incentives for bias, but differ from our paper in various respects.

Note that MacLeod (2003) and later on Rajan and Reichelstein (2006, 2009) and Budde and Hofmann (2024) acknowledge the principal's incentive to downward bias the report in a one shot or finitely repeated game. In order to solve this problem, they assume that the principal can commit to pay a pre-specified bonus, that is either given to the agent or to a third party. Doing so fully removes the principal's incentive to deny the agent his payment and effectively results in a no-bias commitment. In our paper this concept is not applicable as the agent's incentive pay is a function of an effort informative signal the principal receives, rather than a lump sum. However, using a different mechanism, we are able to show that some commitment is possible. Incentives to bias are not completely erased but agency costs decrease.
Moreover, MacLeod (2003) and also Sebald and Walzl (2015), assume that the agent is able to impose costs on the principal, if his evaluation is bad. This threat of conflict trades off the principal's incentive for downward bias and, in a setting with a limited number of available ratings, leads to compressed evaluation results.

Suvorov and van de Ven (2009) and Zábojník (2014) assume that the principal obtains private information about the agent's ability throughout the game and uses performance evaluation to communicate this information to the agent. Positive news regarding capability motivates additional effort, which in turn triggers leniency. Both studies therefore use a setting that not only requires asymmetric information with regard to the agent's capability, but assumes that the principal is the privately informed party. We consider this assumption as not particularly intuitive. Rather, one would typically expect that the agent is better informed about his own ability than the principal.

To sum up, our paper contributes to the literature in two ways: First, we introduce a novel type of commitment-mechanism to help reduce agency costs with SPE. Second, we focus on (behavioral) effects from SPE-specific preferences as the main drivers of reporting behavior. In contrast to previous literature, this implies that we neither need to assume a threat of conflict nor private information of the principal to explain empirically observed patterns of bias.

The paper is structured as follows. Section 2 introduces the model. In section 3 we present results that arise with objective performance measurement and serve as our benchmark in what follows. Section 4 derives solutions for the SPE-setting with sequentially optimal bias choice. Section 5 considers the adapted setting assuming an ex ante optimal bias. Section 6 focuses on the type of biases predicted by our model. Finally, section 7 concludes.

2 Model

We use a single period LEN principal-agent model. The course of the game is presented in figure 1.

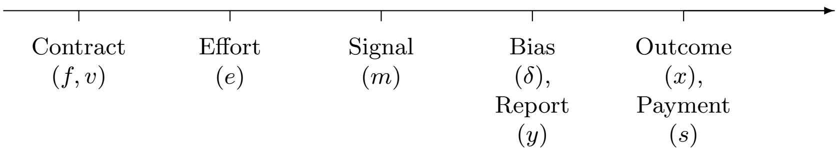

Figure 1: Timeline of the agency.

A risk-neutral principal hires a risk-averse agent to contribute to a newly created project. The agent's effort e increases the project outcome by $x = ae$, where a reflects the agent's productivity. We assume, however, that the project is a complex good or service. Therefore, the agent's individual contribution cannot be measured separately and thus cannot be used for contracting. As an alternative, the principal applies a subjective assessment to evaluate the performance of her employee. Formally, she receives a private signal

$$m = e + \varepsilon, \tag{1}$$

which is based on the agent's effort but also affected by some random noise $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. The signal can be regarded as the aggregated insights the principal gains from work related encounters with the agent over a period. Due to the noise term, these insights are not necessarily accurate and can be outright misleading, too.

Using her signal of the agent's performance, she writes a report to be sent to human resources which denotes

$$y = m + \delta. \tag{2}$$

As the principal has discretion over the evaluation report, she is able to add a bias δ that adjusts the evaluation in her favor. More precisely, the principal can manipulate the evaluation and either up- or downgrade the report y conditional on signal m. It is common knowledge that the evaluation can be distorted. However, the exact manipulation is private information of the principal.

Once the report is sent to human resources, the rating becomes verifiable for third parties. Thus, an incentive contract can be written on the report.[1] The contract has the form

$$s = f + vy, \tag{3}$$

where f is the fixed wage and v is the incentive rate.

The agent's utility increases in his compensation and decreases in disutility from providing effort. To reflect the specifics of SPE, we include an additional factor, $\theta_A = \omega(y - e)$, into the agent's utility function. It captures what Köszegi and Rabin (2006, 2007) describe as expectation based reference dependent preferences. The agent's self assessment, which equals his actual privately known effort, constitutes the reference point. Comparing his effort e with the official assessment of his work y, he feels a psychological gain or loss (see also Daido and Murooka 2016). The strength of this preference is captured by $\omega > 0$. An under-evaluation, tantamount to a negative difference, clearly results in a psychological loss. It is not only regarded as an inaccurate assessment per se, but as an unjustified criticism or reproach that causes disutility. The psychological gain we presume to result from over-evaluation might be less intuitive. Clearly both, over- and under-evaluation harm a possible accuracy preference of the agent and can be perceived as unfair. In line with that, e.g. Prendergast and Topel (1996) and Kamphorst and Swank (2015) argue that continuous praise, that arises largely independent from actual good performance, can demotivate agents. However, it is also documented that evaluations are not only used to provide effort incentives but crucially affect job assignment decisions and thus career perspectives (Prendergast 2002). We presume that the positive utility effects from improved job

[1] The scenario of subjective impressions leading to a verifiable report that serves as a performance measure may fit to the evaluation of a white-collar employee at the lower or middle management level (see Giebe and Gürtler 2012, Golman and Bhatia 2012 or Grund and Przemeck 2012 for similar approaches).

perspectives by far dominate a possible disutility from undeserved praise, justifying that over-evaluation results in an overall psychological gain.[2]

Including this aspect, the agent's exponential utility function is given by:

$$U_A = -\exp[-r(s + \theta_A - c_A)]. \tag{4}$$

Here $r > 0$ is the Arrow-Pratt measure of absolute risk aversion. s is the agent's compensation as defined above and $c_A = \frac{e^2}{2}$ is the agent's disutility from providing effort. It follows directly that the report y affects the agent's utility via its effect on pay and via the SPE-specific effect.

Due to the LEN-assumptions, the agent's expected utility can be expressed through the following certainty equivalent

$$\begin{aligned} CE &= E[s + \theta_A - c_A] - \frac{r}{2} \cdot Var[s + \theta_A - c_A] \\ &= f + v[e + E(\delta)] + \omega E(\delta) - \frac{e^2}{2} - \frac{r}{2}(v + \omega)^2 \cdot Var(\varepsilon + \delta). \end{aligned} \tag{5}$$

It should be noted at this point, that the LEN model imposes fairly restrictive assumptions. Most important, only linear contracts are considered no matter whether the optimal contract is linear or not. Several researchers criticized its extensive use in the literature on this basis. Others, in contrast, emphasized that the assumptions profoundly help to keep the model tractable. We follow the latter opinion, arguing that while the restrictive assumptions, specifically linearity, allow us to derive explicit results, the insights gained are unlikely to be confined to linear structures (see Christensen and Feltham 2005, p.153).

The principal is risk neutral in our model and thus maximizing expected utility is equivalent to expected value maximization. Quite commonly, her utility increases in outcome and decreases in compensation paid to the agent. In addition, and somewhat parallel to our considerations for the agent, we include an additional factor θ_P that reflects specific effects arising with SPE.
Precisely, we define
$\theta_P = \frac{\delta^2}{2} + \psi(y - \widehat{e})^2$.

The first factor, $\frac{\delta^2}{2}$, reflects effort costs that are expected to arise from putting together a biased but still convincing and well founded report (Prendergast and Topel 1996; Prendergast 2002).

[2] This is also in line with empirical findings, e.g. in Bol (2008). She finds that a leniency bias positively affects employees' future performance, indicating a motivating effect of positive evaluations, even if subject to bias.

Alternative explanations are costs for covering ones tracks or costs related to the risk to be caught (see Prendergast 2002). This type of costs is well established in alternative scenarios, e.g. settings in which the agent can bias a performance measure. With SPE, however, costs pertain to the principal.

The second factor, $\psi(y - \widehat{e})^2$, captures disutility that arises as the principal observes a signal, but is aware of the fact that the signal is imperfect. Specifically, the principal gets an impression about the agent's performance over the period (m), but also forms expectations about the agent's effort in equilibrium ($\widehat{e}$). If the signal differs from her expectations, she is aware that she might be missing something. Assuming that the principal has a personal preference for accurate and truthful reporting as described in Grund and Przemeck (2012) and Golman and Bhatia (2012), any assessment y that differs from her own beliefs about the agent's true performance, results in a disutility. ψ captures the strength of this effect. Including all aspects, the expected utility function of the principal equals

$$E[\Pi] = E[x - s - \theta_P] = ae - f - v[e + E(\delta)] - E[\psi(y - \widehat{e})^2 + \frac{\delta^2}{2}]. \tag{6}$$

Thus, the principal maximizes the sum of her expected net payoff, reduced by a SPE-effect, θ_P. Recall that $x = ae$ was defined above with a reflecting the agent's productivity of effort. We assume that a is sufficiently high to ensure that it is optimal for the principal to motivate (positive) effort.[3] From an ex ante perspective, δ is a random variable as it is chosen conditional on the observation of m later on. Importantly, subjective performance measurement in our model not only affects the utility functions of the principal and the agent, it also provides the principal with an additional decision variable δ besides the incentive rate v and fixed pay f.

3 Benchmark: objective performance evaluation

Before we derive the effects of subjective performance evaluation within the model described above, we present solutions to a benchmark setting in which we assume that an objective measure is available for contracting.

In this setting the option to bias along with all other SPE-effects on the agent's and the principal's utility are absent. However, the agent's contribution to output, x, is still considered to be

[3] To ensure that $e > 0$ holds in equilbrium we require $a > \frac{(1+r\sigma_\varepsilon^2)\omega}{1+2\psi}$.

non-contractible. To render the settings comparable, the performance measure available equals the signal introduced in section 2 above. Summing up, we consider $m = e + \varepsilon$ to be an objective measure. It follows that $\delta = \omega = \psi = 0$ holds such that $y = m$.

The principal's optimization problem can be stated as follows

$$\max_{f,\ v}\ E[\Pi] = E[x - s] \tag{7}$$

subject to

$$CE \geq CE_0. \tag{8}$$

$$e \in \underset{e''}{\operatorname{argmax}}\ CE(e''). \tag{9}$$

The agent's certainty equivalent has to cover his reservation wage CE_0. To simplify notation we normalize CE_0 to zero without loss of generality in this and all upcoming settings.

As the above problem boils down to the standard LEN-setting, we present solutions in Lemma 1 below but relegate their derivation to the proof in the appendix.

Lemma 1:

With objective performance measurement and thus in the absence of SPE-driven utility effects the decision variables and the resulting objective function value are given as:

$$v^* = \frac{a}{1 + r\sigma_\varepsilon^2}, \tag{10}$$

$$e^* = \frac{a}{1 + r\sigma_\varepsilon^2}, \tag{11}$$

$$E[\Pi^*] = \frac{a^2}{2(1 + r\sigma_\varepsilon^2)}. \tag{12}$$

Proof: See the appendix.

Note that in this benchmark setting agency costs arise solely from the well known risk and incentive trade-off. In order to motivate effort, the principal needs to impose compensation risk on the agent. Doing so, however, results in a suboptimal allocation of risk, given that the principal is risk neutral and the agent is risk averse. Optimal incentives, along with optimal risk exposure, are larger, the higher the agent's productivity, a, but lower, the larger the cost of risk exposure, reflected in r and σ_ε^2. Accordingly, optimal effort, incentive rate, and expected payoff increase in a, but drecrease in r and σ_ε^2 as shown in Lemma 1.

4 Subjective performance evaluation

In this section we consider the model introduced in section 2. In contrast to the benchmark, the evaluator is now able to bias the report and SPE-specific effects become relevant. Importantly, we assume that the supervisor picks the bias δ sequentially optimal after signal m has been observed. Technically, this adds a second incentive constraint to our problem as stated below.

$$\max_{f,v} \; E[\Pi] = E[x - s - \theta_P] \tag{13}$$

subject to

$$CE \geq 0 \tag{14}$$

$$e \in \operatorname*{argmax}_{e''} CE(e'') \tag{15}$$

$$\delta \in \operatorname*{argmax}_{\delta''} E[\Pi(\delta'')|f, v, \widehat{e}, m]. \tag{16}$$

The choice of reporting bias is the final decision to be made in the game. Given an incentive contract with parameters v and f, the principal receives signal m about the agent's performance. The agent's effort is not observable to her, however, she forms a conjecture, $\widehat{e}$, about it. Her objective function now has the form

$$\begin{aligned} \max_{\delta} \; E[\Pi|f, v, \widehat{e}, m] &= E[x - s - \theta_P|f, v, \widehat{e}, m] \\ &= a\widehat{e} - f - v(m + \delta) - \psi(m + \delta - \widehat{e})^2 - \frac{\delta^2}{2}. \end{aligned} \tag{17}$$

Optimization over δ yields

$$\delta(m) = -\frac{2\psi(m - \widehat{e}) + v}{1 + 2\psi}. \tag{18}$$

Note that the principal chooses the bias trading off the marginal effect of her choice on the agent's pay and on her own utility from SPE-effects.

Any increase in δ increases payment to the agent at a rate of v. Accordingly, (18) decreases in v. Reflecting her truth-telling preference, the principal intends to keep $\psi(m + \delta - \widehat{e})^2$ small. δ thus decreases in $m - \widehat{e}$. Intuitively, observing a higher (lower) than expected m hints towards a positive (negative) ε and thus an overly positive (negative) assessment. Aiming at a correct evaluation, the principal picks δ to counter such outcomes. In addition, her personal disutility from biasing, $\frac{\delta^2}{2}$, keeps her from picking an extensive bias, no matter whether positive or negative.

Importantly, the sequentially optimal choice of the bias implies that the principal can neither use δ to control the agent's effort choice, nor will she consider $\delta's$ effect on the agent's exposure to risk or his utility from being over- or under-valued.

In the next step we substitute the bias derived in (18) into the agent's certainty equivalent. Within the bias expression, the principal's conjecture about effort remains present, as effort is unobservable to the principal. Furthermore, as signal m is not realized at this stage, it needs to be considered a stochastic variable. The agent's certainty equivalent then has the form

$$\max_{e}\ CE(\delta(m)) = f + v(e - \frac{2\psi(e-\widehat{e})+v}{1+2\psi}) - \frac{\omega[2\psi(e-\widehat{e})+v]}{1+2\psi} - \frac{e^2}{2} - \frac{r(v+\omega)^2\sigma_{\varepsilon}^2}{2(1+2\psi)^2}. \tag{19}$$

Optimization yields

$$e = \frac{v-2\psi\omega}{1+2\psi}. \tag{20}$$

Contrasting (20) to the benchmark result of $e = v$, we observe that an increase in incentive rate v still increases effort, but at a lower rate. The reason is that with subjective performance measurement additional effort no longer translates into a one by one increase in performance measure y. Rather, for a given conjecture $\widehat{e}$ any additional effort provided by the agent has an increasing direct effect on y via e, but also an indirect decreasing effect via δ. It follows that the principal's option to bias the report reduces the agent's ability to increase his payoff by performing effort and thus his willingness to do so. Put another way, it becomes harder for the principal to motivate effort via an incentive contract. As a consequence, a higher incentive rate v is needed with SPE in order to motivate the same effort as opposed to a setting with objective performance measurement. In that sense the incentive problem gets harder. Interestingly, the agent's effort decreases in ω, which measures the strength of the agent's preference for over- and dislike for under-evaluation. To get the intuition for this result, note that the agent's personal benefits from subjective evaluation increase in δ but δ decreases in e. Thus, any increase in ω, c.p., triggers a reduction in effort.

The agent's incentive rate is to be determined next. Technically, the binding participation constraint and the incentive constraints for the optimal bias and the optimal effort are substituted into the principal's objective function (13). As the principal anticipates the agent's effort correctly in equilibrium, the real effort replaces the conjecture of effort.

$$\begin{aligned}\max_{v}\ E[\Pi(e,\delta)] &= E[x-\theta_P+\theta_A]-c_A-\frac{r}{2}\cdot Var[s+\theta_A]\\ &= \frac{a(v-2\psi\omega)}{1+2\psi}-\frac{\psi(\sigma_\varepsilon^2+v^2)}{(1+2\psi)^2}-\frac{4\psi^2\sigma_\varepsilon^2+v^2}{2(1+2\psi)^2}\\ &- \frac{v\omega}{1+2\psi}-\frac{(v-2\psi\omega)^2}{2(1+2\psi)^2}-\frac{r\sigma_\varepsilon^2(v+\omega)^2}{2(1+2\psi)^2}. \end{aligned} \tag{21}$$

Optimization yields the solution for v' presented in Lemma 2. Somewhat similar to the benchmark setting, the incentive rate is chosen to trade off risk and incentives in the agency. However, as the principal anticipates her own future behavior, the option to bias does affect the optimal incentive contract, too. More precisely, the principal realizes, that her choice of v will affect her future choice of δ. She includes this knowledge into her contracting problem and chooses contracting variables accordingly. Note that from (18), expected δ is fully determined by choosing v (actual δ will differ as it is chosen conditional on m). Inserting v' into the expressions for e and δ derived above we obtain (23)-(24).

Lemma 2:

With SPE the equilibrium values for the decision variables and the resulting objective function value are given as:

$$v' = \frac{a(1+2\psi)-\omega(1+r\sigma_\varepsilon^2)}{2+2\psi+r\sigma_\varepsilon^2}, \tag{22}$$

$$e' = \frac{a-(1+2\psi+r\sigma_\varepsilon^2)\omega}{2+2\psi+r\sigma_\varepsilon^2}, \tag{23}$$

$$\delta' = \frac{-a(1+2\psi)-2\varepsilon\psi(2+2\psi+r\sigma_\varepsilon^2)+\omega(1+r\sigma_\varepsilon^2)}{(1+2\psi)(2+2\psi+r\sigma_\varepsilon^2)}, \tag{24}$$

$$E[\Pi'] = \frac{a^2(1+2\psi)-2\psi\sigma_\varepsilon^2(2+2\psi+r\sigma_\varepsilon^2)-[2a(1+2\psi)+2\psi\omega](1+2\psi+r\sigma_\varepsilon^2)\omega+\omega^2}{2(1+2\psi)(2+2\psi+r\sigma_\varepsilon^2)}. \tag{25}$$

Proof: See the appendix.

With the solutions from Lemma 1 and Lemma 2 in place, we are able to compare both settings.

Proposition 1:

Contrasting solutions from the benchmark setting and the SPE-setting we find that *(i)* $E[\Pi^*] > E[\Pi^{'}]$

(ii) $v^* \gtreqless v^{'}$, $e^* > e^{'}$.

Proof: See the appendix.

Proposition 1 (i) states that the principal's expected payoff decreases with SPE as compared to the benchmark. Accordingly, she would prefer an objective measure if available.

Several facets of SPE already discussed above give rise to this result. To build on intuition, we summarize the main drivers in terms of costs and benefits below.

First, direct costs of bias arise as any bias constitutes additional costs for the principal (θ_P). In addition, we observe from Lemma 2 that $E(\delta') = -\frac{v'}{1+2\psi} < 0$.[4] As a consequence $E(\theta_A) = \omega E(\delta') < 0$ turns out as another direct cost from bias. Second, SPE has an increasing effect on the agent's exposure to risk due to θ_A and a decreasing effect that follows from $\frac{\partial \delta}{\partial \varepsilon} < 0$. As a consequence costs from risk exposure might be larger, but also smaller, with SPE. Third, incentive provision gets harder with SPE and thus optimal effort decreases. In fact, as shown in Proposition 1 (ii), any increase in the incentive rate that arises in equilibrium, is insufficient to make up for the reduced incentive effects. Put differently, e' turns out to be smaller than e^* even though v' can either be smaller or larger than v^*. Fourth, with SPE the incentive rate is not solely chosen to optimally trade off risk and incentives as in the benchmark, it is also affected by the principal's incentives to bias. As a consequence the risk and incentive trade-off gets distorted causing further agency costs.

5 Subjective performance evaluation with ex ante optimal bias

As has been demonstrated already above, part of the (additional) agency costs associated with SPE arises from our assumption that the principal decides about the bias late in the game. In particular, doing so implies that she ignores any effect on the agent's exposure to risk and on effort incentives when determining the bias. Given this insight, we now consider a setting in which the principal can credibly commit herself to an ex ante optimal bias choice. Importantly,

[4] Note that (24) can be rewritten as $\delta' = -\frac{2\psi\varepsilon + v'}{1+2\psi}$. As $E(\varepsilon) = 0$ it follows that $E(\delta') = -\frac{v'}{1+2\psi}$ holds.

the optimal bias, no matter whether from an ex post or an ex ante perspective, is to be chosen conditional on signal m, which is observed late in the game. In other words, it is never optimal for the principal to ignore m when deciding about δ or, equivalently, to pick δ previously to her observation of m. Accordingly, we assume that the principal can commit to a mechanism, ensuring that δ is picked as some pre-specified (linear) function of m.

$$\delta(m) = km + b \tag{26}$$

where k and b are chosen along with the contracting parameters f and v.

To provide an example how to implement this mechanism, assume that a two step evaluation procedure is used and communicated to or observed by the employee.[5] In the first step, the principal sets up a reporting procedure at the beginning of the game that pre-specifies in which way the employee's accomplishments enter the report and translate into an overall opinion (y). In a second step, she delegates the noisy recording of these achievements to a third party, who has no stake in distorting the results.[6] Doing so ensures that (a) the principal determines ex ante how m is transformed into the report y and (b) that she can neither omit any relevant information nor invent some to distort m itself in an ex ante suboptimal manner. The third party might be a personal assistant or, depending on the employee's type of job, some automated process, e.g. a software that collects performance relevant data on the employee and aggregates them to produce the signal. Also, a combination of both would be feasible.

In this setting the optimization problem of the principal can then be stated as

$$\max_{f,\ v,\ k,\ b} \ E[\Pi] = E[x - s - \theta_P] \tag{27}$$

subject to

$$CE \geq 0 \tag{28}$$

$$e \in \operatorname*{argmax}_{e''} CE(e''). \tag{29}$$

[5] The underlying idea is somewhat similar to Bol et al. (2016). They find experimental evidence that sophisticated control system design can help to improve the evaluator's performance, while we show that a cleverly structured reporting process affects an evaluator's biasing behavior in an overall benefical way.

[6] Using delegation as a means to credibly commit to an otherwise implausible behavior has already been suggested in Melumad and Mookherjee (1989).

Accordingly, the principal decides about the determinants of δ, k and b, simultaneously with the contracting parameters at the beginning of the game. Thus δ is fully determined by the realization of m and the final actual choice in the game is the agent's effort choice. The agent picks his effort in order to maximize his certainty equivalent, given that contracting parameters are known and so are k and b, given he has been informed about the evaluation process. With the incentive constraint in place, the principal maximizes expected payoff w.r.t. v, k, and b. The procedure is structurally similar to the benchmark model. Therefore, we relegate the details to the appendix.[7] Results are presented in Lemma 3.

Lemma 3:

If the principal can commit to choose the bias conditional on m according to a pre-specified mechanism, the optimal levels for the decision variables and the resulting objective function value are given as:

$$v^{**} = \frac{a(1+2\psi) + 2\psi\omega - r\sigma_\varepsilon^2\omega}{1 + r\sigma_\varepsilon^2}, \tag{30}$$

$$\delta^{**} = \frac{\omega - 2\varepsilon\psi}{1 + 2\psi}, \tag{31}$$

$$e^{**} = \frac{a - r\sigma_\varepsilon^2\omega}{1 + r\sigma_\varepsilon^2}, \tag{32}$$

$$E[\Pi^{**}] = \frac{a^2(1+2\psi) - 2a(1+2\psi)r\sigma_\varepsilon^2\omega + \omega^2 - 2\psi\sigma_\varepsilon^2(1 + r(\sigma_\varepsilon^2 + \omega^2))}{2(1+2\psi)(1 + r\sigma_\varepsilon^2)}. \tag{33}$$

Proof: See the appendix.

Interestingly, inserting k^{**} as derived in the proof of Lemma 3, into the agent's optimal effort choice (63) results in

$$e = \frac{v - 2\psi\omega}{1 + 2\psi}. \tag{34}$$

This expression equals the one obtained in (20) in section 4, indicating that the effort choice as a function of v is independent from the timing of the principal's bias choice. Put another way, every difference in effort choice is completly driven by the difference in the incentive rate offered with and without commitment. Naturally, the interpretation of (20) provided in section 4 extends to (34).

To provide insights regarding the difference in the bias choice in both settings, it helps to express

[7] See proof of Lemma 3.

the sequentially optimal bias, δ', as a linear function of m as well. We do so in Corollary 1.

Corollary 1:

Inserting k^{**} and b^{**} into 26, we obtain

$$\delta^{**}(m) = k^{**}m + b^{**} = -\frac{2\psi}{1+2\psi}m + \frac{2a\psi + [1 + (1-2\psi)r\sigma_\varepsilon^2]\omega}{(1+2\psi)(1+r\sigma_\varepsilon^2)}. \tag{35}$$

Restating (24) results in

$$\delta'(m) = k'm + b' = -\frac{2\psi}{1+2\psi}m + \frac{-a + [1 + r\sigma_\varepsilon^2 - 2\psi(1+2\psi+r\sigma_\varepsilon^2)]\omega}{(1+2\psi)(2+2\psi+r\sigma_\varepsilon^2)}. \tag{36}$$

Further

$$b^{**} = \frac{2a\psi + [1 + (1-2\psi)r\sigma_\varepsilon^2]\omega}{(1+2\psi)(1+r\sigma_\varepsilon^2)} > \frac{-a + [1 + r\sigma_\varepsilon^2 - 2\psi(1+2\psi+r\sigma_\varepsilon^2)]\omega}{(1+2\psi)(2+2\psi+r\sigma_\varepsilon^2)} = b' \tag{37}$$

holds true.

Proof: See the appendix.

Corollary 1 shows that $\delta^{**} > \delta'$ holds for any given m and thus ε. This implies that the ex post choice of the bias is suboptimal ex ante and that δ' is distorted downwards. Moreover, we observe that the bias choice differs by a constant amount equal to the difference in b for any given m. The slope of both functions, (35) and (36), in contrast, is identical. It follows that there is no distortion in the principal's reaction at the margin. With any increase (decrease) in m, she decreases (increases) δ at the same rate, no matter whether δ is chosen ex ante or ex post optimal. This finding somewhat simplifies the mechanism proposed above even further. In fact, within the first step, it suffices to pre-specify a lump sum that is added no matter which signal is observed. With this constant in place, there is no incentive for the principal to pick the rate in suboptimal fashion later on.

Having derived the results in Lemma 3, we are now able to juxtapose them to (i) the no commitment setting presented in section 4 and (ii) the benchmark from section 3.

Proposition 2:

(i) Comparing results from SPE with and without ex ante optimal bias choice we obtain

$E[\Pi^{**}] > E[\Pi^{'}]$, $v^{**} > v^{'}$, $e^{**} > e^{'}$, $\delta^{**} > \delta^{'}$.

(ii) Comparing the benchmark results and SPE with ex ante optimal bias we obtain $E[\Pi^{*}] \gtreqless E[\Pi^{**}]$, $v^{*} \gtreqless v^{**}$, $e^{*} > e^{**}$.

Proof: See the appendix.

Proposition (2) (i) follows directly from our previous findings. Formally, the optimization problem in section 4 contains an additional constraint regarding the choice of δ as opposed to the one in this section. Therefore, the payoff is smaller. The underlying reasons have been mostly established already. A sequentially optimal choice of bias implies that the principal ignores any effects her choice might have on the agent's utility and effort incentives, which results in a downward distorted bias. However, she anticipates her own future behavior when picking the contracting parameters. As δ' is decreasing in the incentive rate, v' is distorted downwards as opposed to v^{**}, in order to mitigate the distortion in the bias. Doing so, however, affects the agent's effort choice. While the agent's equilibrium effort conditional on v is identical in both settings, as stated above, downward distortion of v' translates into e' smaller than e^{**}. Overall, a sequentially optimal bias choice results in agency costs from the distortion in bias and, in addition, in agency costs due to distortion in the contracting parameter choice. Both reduce the payoff attainable for the principal as compared to the ex ante optimal bias setting.

Recalling that SPE with a sequentially optimal bias choice is detrimental as compared to objective performance measurement (Proposition 1), we observe in Proposition 2 (ii), that this result does not hold unequivocally with ex ante optimal bias. Precisely, there exist parameter combinations, for which SPE with ex ante optimal bias results in a payoff larger than with objective performance evaluation. A necessary condition for this to arise is identified in Corollary 2.

Corollary 2:

From Proposition 2 (ii) we know that $E[\Pi^{*}] \gtreqless E[\Pi^{**}]$.

For $E[\Pi^{*}] < E[\Pi^{**}]$ *we require*

$$\omega > \sqrt{\frac{2\sigma_\varepsilon^2\psi(1+r\sigma_\varepsilon^2)}{1-2\sigma_\varepsilon^2 r(1+\psi+r\sigma_\varepsilon^2)}}. \tag{38}$$

If (38) is violated, $E[\Pi^{*}] > E[\Pi^{**}]$ *holds.*

Proof: See the appendix.

The driving force behind this result is that commitment leads to $E(\delta^{**}) = \frac{\omega}{1+2\psi} > 0$ in equilibrium. Consequently, and in contrast to the sequentially optimal bias setting, $E(\theta_A) = \omega E(\delta^{**}) > 0$ arises, tantamount to an expected benefit from over-evaluation that increases the agent's utility. If this benefit is sufficiently high to outweigh the costs from θ_P and potential increases in risk exposure, the principal's payoff increases with SPE. For this to happen, the agent needs to greatly benefit from an over-evaluation, reflected in a large ω. The principal's truth-telling preference, in contrast, needs to be sufficiently moderate, tantamount to a small ψ. Finally, costs of risk, as reflected in the variance of ε and the parameter of absolute risk aversion r need to be low. All of this is observed directly from (38) of Corollary 2. Contrasting the results from (ii) with regard to incentive rates and effort to those in Proposition 1, we observe that they are qualitatively similar. Even if the incentive rate with subjective evaluation might beat the one with objective evaluation, this never compensates for the reduced incentive effect and thus results in reduced effort in equilibrium.

6 Leniency bias and centrality bias

As already mentioned in the introduction, there is the vast amount of empirical literature stating that SPE tends to provoke two types of biases: the leniency bias and the centrality bias.
A leniency bias arises if the principal systematically distorts her report upwards. In terms of our model this would imply that the expected value of the signal, m, is smaller than the expected value of the report y remitted to human resources.[8] $E(m) < E(y)$, however, is equivalent to $E(\delta) > 0$.

Proposition 3:
(i) If the principal chooses her bias sequentially optimal, an expected under-evaluation arises.
(ii) If the principal chooses her bias ex ante optimal, a leniency bias is present.

The results in Proposition 3 can be derived directly from in Lemma 2 and 3. As for Proposition 3 (i) we already stated in section 4 that $E(\delta^{'}) < 0$ holds and thus a systematic under-evaluation is present. For (ii), we need to determine the expected value of δ^{**} as derived in Lemma 3. Doing so we obtain $E(\delta^{**}) = \frac{\omega}{1+2\psi} > 0$. It follows that a leniency bias arises endogenously in our model, if the principal is able to commit to an ex ante optimal biasing behavior. If this is

[8] See e.g. Bol and Smith (2011), Moers (2005), and Golman and Bhatia (2012) for similar definitions.

not possible, no leniency bias occurs.

It should be noted, however, that over- as well as under-evaluations can arise in both settings. In fact, whether a positive or negative δ is picked, depends on the realization of m and in turn the noise term ε. If, for instance, ε is "sufficiently small" an over-evaluation arises in both settings. The major difference between settings is that with a sequentially optimal bias choice this condition is much tighter than with an ex ante optimal choice. In fact, with commitment, a small positive ε still leads to an over-evaluation. Without commitment, in contrast, ε has to be negative for an over-evaluation to arise. As $E(\varepsilon) = 0$ it follows directly that over-evaluation arises in expectation with commitment, while under-evaluation is present in expectation with no commitment. Given that empirical studies find almost unequivocal evidence for a leniency bias, this result might be an indication, that firms are indeed capable to implement mechanisms that result in ex ante optimal bias choices of their supervisors.

A centrality bias entails that the performance evaluation is somewhat compressed around some norm, such that the full scale of evaluations is not appropriately used. In terms of our model, this implies that δ is picked in such a way that y is less volatile than m, tantamount to $Var(y) < Var(m)$.[9] This is indeed the case in both our settings as is stated in Proposition 4.

Proposition 4:

A centrality bias arises in equilibrium no matter whether the bias is picked ex ante or sequentially optimal:

$Var[m^{**}] = Var[m'] = \sigma_\varepsilon^2$ *and*

$Var[y^{**}] = Var[y'] = \frac{\sigma_\varepsilon^2}{(1+2\psi)^2}$

implying that $Var[m'] = Var[m^{**}] > Var[y'] = Var[y^{**}]$ *holds.*

Proof: See the appendix.

A centrality bias is not only present in both settings, it is also equivalent in both. The underlying reasons for the latter are deductible from Corollary 1 right away. Glancing back, we can replace m by $e + \varepsilon$.[10] $Var(m) = Var(\varepsilon)$ always holds. As ε is the only random variable in (35) and (36) it follows directly that $Var(\delta') = Var(\delta^{**}) = Var(\frac{2\psi\varepsilon}{1+2\psi})$. This extends to $Var(y^{**}) = Var(\varepsilon + \delta^{**}) = Var(\varepsilon + \delta') = Var(y')$.

The centrality bias itself results from δ being a decreasing function in ε. Intuitively, the principal

[9] For a similar definition see e.g. Bol and Smith (2011) and Trapp and Trapp (2019).

[10] That implies that we can write (35) and (36) as $\delta^{**} = -\frac{2\psi}{1+2\psi}(e^{**} + \varepsilon) + b^{**}$ and $\delta' = -\frac{2\psi}{1+2\psi}(e' + \varepsilon) + b'$, respectively.

forms a conjecture about the agent's effort, which turns out to be correct in equilibrium. Using this conjecture, she derives ε having observed m. Due to her truth-telling preference, she dislikes an evaluation that differs from the effort she conjectures and thus picks the bias that countervails any positive or negative realisation of ε. The strength of this effect critically depends on the strength of her truth-telling preference, reflected in ψ. Note that the decrease of δ^{**} and δ', in (35) and (36), respectively, is stronger, the larger ψ. While the choice of the reporting bias, as discussed above already, depends on a number of factors, the principal's reaction to the perceived realisation of ε hinges on her truth-telling preference alone. This extends to the volatility of y. The larger ψ, the more the principal's choice of bias aims at correcting for noise in the evaluation and the smaller $Var(y)$ as compared to $Var(m)$.

To further illustrate the above results, we present two numerical examples in Figure 2. Assume $r = 0.7$, $\psi = 0.3$, $\omega = 0.1$, $\sigma_\varepsilon = 0.15$, and $a = 0.5$ for both, the ex ante optimal bias choice setting (a) and the sequentially optimal bias choice setting (b).

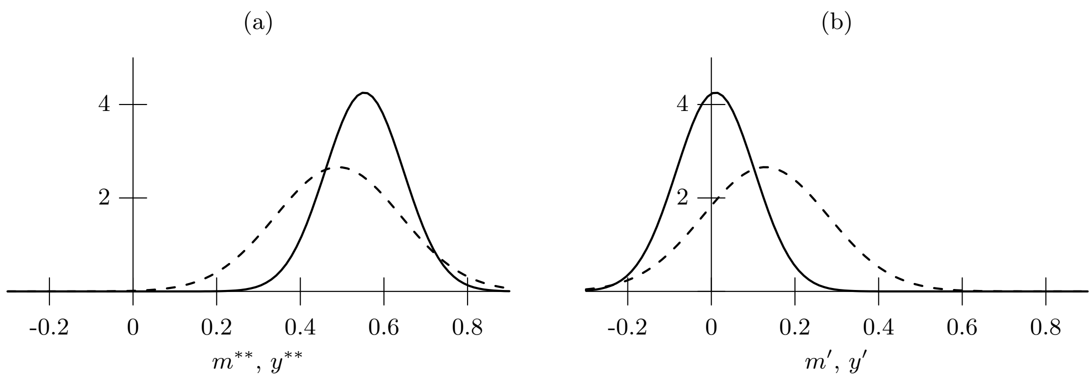

Figure 2: Probability density functions of signals m^{**}, m' (dashed) and reports y^{**}, y' (solid).

It is easy to observe that $Var[m] > Var[y]$ holds under (a) and (b). The principal's optimal evaluation reports are less volatile than the signals they are based on. This is what constitutes a centrality bias. However, while under commitment to an ex ante optimal bias (a) a leniency bias, $E[m^{**}] < E[y^{**}]$, can be observed, without this commitment (b) shows the expected downward distortion, $E[m'] > E[y']$.

7 Conclusion

In this paper we evaluate incentive effects related to subjective performance evaluation within an agency setting. We use a model setup tailored to map important features of SPE. First and foremost, we allow for the principal to bias her evaluation report, which adds an additional choice variable late in the game. Second, we assume that there are SPE-specific effects on the utility functions of both the principal and the agent. With regard to the principal, a bias creates additional costs as it violates her truth-telling and/or accuracy preference and requires effort. With regard to the agent, a reporting bias results in a benefit in case of over-evaluation, but also in costs from under-evaluation.

We contrast this framework to a benchmark setting in which performance evaluation is based on an objective measure. We find that SPE is strictly inferior to objective performance evaluation. Therefore, the principal would go for objective measurement, whenever available. Agency costs from SPE result from costs of reporting bias itself but also from the sequentially optimal choice of the bias. The supervisor's perceived inability to commit herself to an ex ante optimal biasing behavior causes a downward distorted choice of bias. In fact, the expected bias turns out to be negative, which imposes an additional (expected) cost from under-evaluation on the agent. The underlying reason is that the principal ignores the effects of her biasing choice on contracting parameters, managerial effort incentives, risk exposure, and the above mentioned utility effects from under- and over-evaluation, when picking the bias sequentially optimal. Acknowledging the detrimental effect of a sequentially optimal bias choice we consider an adapted setting, in which the supervisor is indeed able to commit herself to an ex ante optimal bias. Naturally, SPE with commitment is strictly superior to SPE without commitment. We also find that with commitment, SPE is no longer dominated by objective performance evaluation. Rather, it becomes superior if the agent's preference for over-evaluation is sufficiently strong and the truth telling preference of the superior and the costs of risk are moderate.

In our model a centrality bias arises endogenously, no matter whether the bias is chosen ex ante or sequentially optimal. This is in line with empirical observations from previous literature as reported above. With regard to the leniency bias, we find that such a bias arises endogenously only if the bias is chosen ex ante optimal. If the supervisor chooses the bias sequentially optimal, an expected downward distortion occurs. Relating these results to the empirical literature that finds rampant evidence for lenient behavior, gives rise to at least two interpretations. One is that supervisors, or their firms, (a) do realize that an ex ante optimal bias choice is beneficial and (b) are able to implement mechanisms that trigger this choice. Alternatively, one might argue that our model considers a supervisor, who is also the residual claimant. The empirical studies conducted, in contrast, do not seem to distinguish between supervisors who loose money when they pay their employees and supervisors who do not. Accordingly one might argue that the observed leniency bias is driven by the latter class of supervisors rather than by the former.

Appendix

Proof of Lemma 1

Once the incentive contract has been signed, the agent maximizes the certainty equivalent of his expected utilitiy equal to

$$\begin{aligned}\max_e \; CE &= E[s] - c_A - \frac{r}{2} \cdot Var[s] \\ &= f + ve - \frac{e^2}{2} - \frac{r}{2} \cdot v^2 \sigma_\varepsilon^2. \end{aligned} \tag{39}$$

Optimizing (39) w.r.t. e we obtain the first order condition

$$\frac{\partial CE}{\partial e} = v - e = 0 \tag{40}$$

and thus $e = v$. Substituting the binding participation constraint (8) into the principal's objective function (7) and inserting the incentive constraint $e = v$ we obtain

$$\max_v \; E[\Pi] = E[x - s] = av - \frac{v^2}{2} - \frac{r}{2} v^2 \sigma_\varepsilon^2. \tag{41}$$

Optimizing the principal's objective function (41) w.r.t. v results in the following first order condition:

$$\frac{\partial E[\Pi]}{\partial v} = a - v - r\sigma_\varepsilon^2 v = 0 \tag{42}$$

Solving for v, we obtain

$$v^* = \frac{a}{1 + r\sigma_\varepsilon^2}. \tag{43}$$

(11) follows from $e = v$.

Checking second-order conditions confirms, that all optimal values are local maxima:

$$\frac{\partial^2 CE}{\partial e^2} = -1 < 0, \tag{44}$$

$$\frac{\partial^2 E[\Pi]}{\partial v^2} = -1 - r\sigma_\varepsilon^2 < 0. \tag{45}$$

Inserting v^* into (41) and collecting terms results in (12).

■

Proof of Lemma 2

Optimizing (17) w.r.t. δ we obtain the first order condition

$$\frac{\partial E[\Pi|f,v,\widehat{e},m]}{\partial\delta} = -v - 2\psi(m+\delta-\widehat{e}) - \delta = 0. \tag{46}$$

Solving for δ we obtain (18). Inserting (18) into the agent's certainty equivalent and noting that $E(m) = e$ we get (19). Optimizing (19) w.r.t. e the first order condition obtained is

$$\frac{\partial CE(\delta(m))}{\partial e} = v - \frac{2\psi v}{1+2\psi} - \frac{2\omega\psi}{1+2\psi} - e = 0 \tag{47}$$

Solving for e results in (20).

Now substituting the binding participation constraint and both incenitve constraints into the objective function or the principal, (13), we get

$$\begin{aligned} E[\Pi(e,\delta)] &= ae - \psi E[(\varepsilon+\delta)^2] - \frac{1}{2}E[\delta^2] + \omega E[\varepsilon+\delta] - \frac{e^2}{2} - \frac{r}{2}Var[f+v(e+\varepsilon+\delta)] \\ &= \quad \frac{a(v-2\psi\omega)}{1+2\psi} - \frac{\psi(\sigma_\varepsilon^2+v^2)}{(1+2\psi)^2} - \frac{4\psi^2\sigma_\varepsilon^2+v^2}{2(1+2\psi)^2} - \frac{v\omega}{1+2\psi} \qquad (48) \\ &- \frac{(v-2\psi\omega]^2}{2(1+2\psi)^2} - \frac{r\sigma_\varepsilon^2(v+\omega)^2}{2(1+2\psi)^2}. \qquad (49) \end{aligned}$$

This equals (21).

Optimizing w.r.t. v and solving the first order condition

$$\frac{\partial E[\Pi(e,\delta)]}{\partial v} = 0 \tag{50}$$

for v results in (22).

Checking corresponding second-order derivatives we get

$$\frac{\partial^2 E[\Pi|f,v,m,\widehat{e}]}{\partial\delta^2} = -2\psi - 1 < 0, \tag{51}$$

$$\frac{\partial^2 CE[\delta(m)]}{\partial e^2} = -1 < 0, \tag{52}$$

$$\frac{\partial^2 E[\Pi(\delta)]}{\partial v^2} = -\frac{2(1+\psi)+r\sigma_\varepsilon^2}{(1+2\psi)^2} < 0. \tag{53}$$

All optimal values constitute local maxima.

Inserting v' into (20) we obtain e'. Considering that $m = e + \varepsilon$ and $e = \widehat{e}$ in equilibrium and inserting into (18) we obtain δ'. Finally, substituting v', e', and δ' into (21) yields (25).

■

Proof of Proposition 1

Taking the first derivative of (25) from Lemma 2 w.r.t. ψ we get

$$\frac{\partial E[\Pi']}{\partial \psi} < 0 \tag{54}$$

It follows directly that $E[\Pi']$ is maximized for $\psi \to 0$ and

$$\lim_{\psi \to 0} E[\Pi'] = \frac{a^2 + \omega^2 - 2a\omega(1 + r\sigma_\varepsilon^2)}{2(2 + r\sigma_\varepsilon^2)} \tag{55}$$

Recall that we assume $a > \frac{\omega(1+r\sigma_\varepsilon^2)}{1+2\psi}$ which implies that $a > \omega$ holds as well. It follows that

$$\frac{a^2 + \omega^2 - 2a\omega(1 + r\sigma_\varepsilon^2)}{2(2 + r\sigma_\varepsilon^2)} < \frac{(a-\omega)^2}{2(2 + r\sigma_\varepsilon^2)} < \frac{a^2}{2(1 + r\sigma_\varepsilon^2)}. \tag{56}$$

As $E[\Pi^*] = \frac{a^2}{2(1+r\sigma_\varepsilon^2)}$ from (12) in Lemma 1, it follows that $E[\Pi^*] > E[\Pi^{'}]$.
Define $\Delta v_{ii} = v^* - v'$. Using (10) from Lemma 1 and (22) from Lemma 2 we get

$$\Delta v_{ii} = \frac{a(1 - 2\psi r\sigma_\varepsilon^2) + (1 + r\sigma_\varepsilon^2)^2\omega}{(1 + r\sigma_\varepsilon^2)[2(1+\psi) + r\sigma_\varepsilon^2]} \gtreqless 0. \tag{57}$$

Define $\Delta e_{ii} = e^* - e'$. Using (11) from Lemma 1 and (23) from Lemma 2 we get

$$\Delta e_{ii} = \frac{a(1 + 2\psi) + (1 + r\sigma_\varepsilon^2)(1 + 2\psi + r\sigma_\varepsilon^2)\omega}{(1 + r\sigma_\varepsilon^2)[2(1+\psi) + r\sigma_\varepsilon^2]} > 0. \tag{58}$$

■

Proof of Lemma 3

Given (26), the agent picks e in order to maximize his objective function

$$\begin{aligned}\max_e \; CE(f, v, k, b) &= E[s + \theta_A - c_A] - \frac{r}{2} \cdot Var[s + \theta_A - c_A] \\ &= f + v[E(y)] + \omega[E(y) - e] - \frac{e^2}{2} - \frac{r}{2} Var[vy + \omega(y - e)]. \end{aligned} \tag{59}$$

Inserting

$$y = m + \delta = e + \varepsilon + k(e + \varepsilon) + b \tag{60}$$

we obtain

$$
\begin{aligned}
\max_{e}\ CE(f,v,k,b) &= E[s+\theta_A-c_A]-\frac{r}{2}\cdot Var[s+\theta_A-c_A]\\
&= f+v[e(1+k)+b]+\omega(ke+b)-\frac{e^2}{2}-\frac{r}{2}(v+\omega)^2(1+k)^2\sigma_\varepsilon^2. \qquad (61)
\end{aligned}
$$

Optimizing w.r.t. e we get the following first order condition:

$$\frac{\partial CE(f,v,k,b)}{\partial e}=v(1+k)+\omega k-e=0. \qquad (62)$$

Solving for e results in

$$e=v+k(v+\omega). \qquad (63)$$

Substituting the binding participation constraint (28) into the principal's objective function and inserting the incentive constraint we obtain

$$
\begin{aligned}
\max_{v,k,b}\ E[\Pi] &= a[v+k(v+\omega)]-\psi[(1+k)^2\sigma_\varepsilon^2+(k(v+k(v+\omega))+b)^2]\\
&-\frac{[k(v+k(v+\omega))+b]^2+k^2\sigma_\varepsilon^2}{2}+\omega[k(v+k(v+\omega))+b]-\frac{[v+k(v+\omega)]^2}{2}\\
&-\frac{r}{2}(v+\omega)^2(1+k)^2\sigma_\varepsilon^2. \qquad (64)
\end{aligned}
$$

Optimizing (64) w.r.t. k, b, and v we identify two stationary points. The first one is characterized by

$$k^{**}=-\frac{2\psi}{1+2\psi} \qquad (65)$$

$$b^{**}=\frac{2a\psi+[1+(1-2\psi)r\sigma_\varepsilon^2]\omega}{(1+2\psi)(1+r\sigma_\varepsilon^2)} \qquad (66)$$

$$v^{**}=\frac{a(1+2\psi)+2\psi\omega-r\sigma_\varepsilon^2\omega}{1+r\sigma_\varepsilon^2}. \qquad (67)$$

The second one arises at

$$k^{+}=-1 \qquad (68)$$

$$b^{+}=\frac{2\psi\omega}{1+2\psi} \qquad (69)$$

$$v^{+}=-\omega-\frac{\sigma_\varepsilon^2}{a+\omega}. \qquad (70)$$

To check for a local maximum we need to evaluate the Hessian

$$H(k,b,v) = \begin{pmatrix} \frac{\partial^2 E[\Pi(k,b,v)]}{\partial k^2} & \frac{\partial^2 E[\Pi(k,b,v)]}{\partial kb} & \frac{\partial^2 E[\Pi(k,b,v)]}{\partial kv} \\ \frac{\partial^2 E[\Pi(k,b,v)]}{\partial bk} & \frac{\partial^2 E[\Pi(k,b,v)]}{\partial b^2} & \frac{\partial^2 E[\Pi(k,b,v)]}{\partial bv} \\ \frac{\partial^2 E[\Pi(k,b,v)]}{\partial vk} & \frac{\partial^2 E[\Pi(k,b,v)]}{\partial vb} & \frac{\partial^2 E[\Pi(k,b,v)]}{\partial v^2} \end{pmatrix}$$

In the three variable case, a local extreme point is a maximum if $(-1)^r \Delta_r(k,b,v) \geq 0$ for $r = 1,2,3$. Where $\Delta_r(k,b,v)$ are the leading principal minors of $H(k,b,v)$.

We start analyzing (k^{**}, b^{**}, v^{**}) as presented in (65)-(67).

The first principal minor equals

$$\Delta_1(k^{**}, b^{**}, v^{**}) = \frac{\partial^2 E[\Pi(k^{**}, b^{**}, v^{**})]}{\partial k^2} = -\frac{(1+2\psi)[A+B+C]}{(1+r\sigma_\varepsilon^2)^2} \tag{71}$$

with

$$\begin{aligned} A &= (\sigma_\varepsilon + r\sigma_\varepsilon^3)^2 + a^2[2 + r\sigma_\varepsilon^2 + 2\psi(\psi - 1) + r\sigma_\varepsilon^2)] \\ B &= 2a[1 + 4\psi(\psi + r\sigma_\varepsilon^2)]\omega \\ C &= (1 + 2\psi + 4\psi^2 + (1+6\psi)r\sigma_\varepsilon + r^2\sigma_\varepsilon^4)\omega^2 \end{aligned}$$

Note that A, B, and C are strictly positive. It follows that $\Delta_1 < 0$ and $(-1)^1\Delta_1 > 0$.

The second principal minor is

$$\Delta_2(k^{**}, b^{**}, v^{**}) = \frac{(1+2\psi)^2[\sigma_\varepsilon^2 + r\sigma_\varepsilon^4 + (1+2\psi)(a+\omega)^2]}{1+\sigma_\varepsilon^2} > 0 \tag{72}$$

and $(-1)^2\Delta_2(k^{**}, b^{**}, v^{**}) > 0$ holds.

Finally, the third pricipal minor equals

$$\Delta_3(k^{**}, b^{**}, v^{**}) = -\sigma_\varepsilon(1+r^2) < 0. \tag{73}$$

It follows that $(-1)^3\Delta_3(k^{**}, b^{**}, v^{**}) > 0$ holds true. Accordingly, $(-1)^r\Delta_r(k,b,v) \geq 0$ holds for $r = 1,2,3$ and the stationary point is a maximum.

For the second stationary point (k^+, b^+, v^+) depicted in (68)-(70) the third leading principal minor equals

$$\Delta_3(k^+, b^+, v^+) = (1+2\psi)(a+\omega)^2) > 0. \tag{74}$$

It follows directly that $(-1)^3\Delta_3(k^+, b^+, v^+) < 0$ and thus a necessary condition for a maximum is violated. Accordingly, (k^{**}, b^{**}, v^{**}) constitutes the only maximum. Inserting the results from (65)-(67) into (64) we get (33).

■

Proof of Corollary 1:

Note that from (18) we can derive

$$\delta' = -\frac{2\psi}{1+2\psi}m + \frac{2\psi\widehat{e} - v}{1+2\psi}. \tag{75}$$

Inserting $v = v'$ and noting that $\widehat{e} = e = e'$ in equilibrium we obtain (36). δ^{**} can be derived by inserting 65 and 66 into 26 resulting in 35.

Calculating the difference between b^{**} and b' and collecting terms we obtain

$$b^{**} - b' = \frac{(1+2\psi+r\sigma_\varepsilon^2)(a+\omega)}{(1+r\sigma_\varepsilon^2)(2+2\psi+r\sigma_\varepsilon^2)} > 0. \tag{76}$$

■

Proof of Proposition 2

(i)

Define $\Delta E[\Pi_i] = E[\Pi^{**}] - E[\Pi^{'}]$. Using (33) from Lemma 3 and (25) from Lemma 2 we get

$$\Delta E[\Pi_i] = \frac{(1+2\psi)(a+\omega)^2}{2(1+r\sigma_\varepsilon^2)[2(1+\psi)+r\sigma_\varepsilon^2]} > 0. \tag{77}$$

Define $\Delta v_i = v^{**} - v^{'}$. Using (30) from Lemma 3 and (22) from Lemma 2 we get

$$\Delta v_i = \frac{(1+2\psi)^2(a+\omega)}{(1+r\sigma_\varepsilon^2)[2(1+\psi)+r\sigma_\varepsilon^2]} > 0. \tag{78}$$

Define $\Delta e_i = e^{**} - e^{'}$. Using (32) from Lemma 3 and (23) from Lemma 2 we get

$$\Delta e_i = \frac{(1+2\psi)(a+\omega)}{(1+r\sigma_\varepsilon^2)[2(1+\psi)+r\sigma_\varepsilon^2]} > 0. \tag{79}$$

Define $\Delta \delta_i = \delta^{**} - \delta^{'}$. Using (31) from Lemma 3 and (24) from Lemma 2 we get

$$\Delta \delta_i = \frac{(a+\omega)}{2(1+\psi)+r\sigma_\varepsilon^2} > 0. \tag{80}$$

(ii)

Define $\Delta E[\Pi_{iii}] = E[\Pi^*] - E[\Pi^{**}]$. Using (12) from Lemma 1 and (33) from Lemma 3 we get

$$\Delta E[\Pi_{iii}] = \frac{(2ar\sigma_\varepsilon^2 - \omega)\omega + 2\psi\sigma_\varepsilon^2[1 + r(\sigma_\varepsilon^2 + 2a\omega + \omega^2)]}{2(1+2\psi)(1+r\sigma_\varepsilon^2)} \gtreqless 0. \tag{81}$$

Define $\Delta v_{iii} = v^* - v^{**}$. Using (10) from Lemma 1 and (30) from Lemma 3 we get

$$\Delta v_{iii} = \frac{r\sigma_\varepsilon^2\omega - 2\psi(a+\omega)}{1+r\sigma_\varepsilon^2} \gtreqless 0. \tag{82}$$

Define $\Delta e_{iii} = e^* - e^{**}$. Using (11) from Lemma 1 and (32) from Lemma 3 we get

$$\Delta e_{iii} = \frac{r\sigma_\varepsilon^2\omega}{1+r\sigma_\varepsilon^2} > 0. \tag{83}$$

■ **Proof of Corollary 2**:

Note that

$$\frac{\partial \Delta E[\Pi_{iii}]}{\partial a} = \frac{r\sigma_\varepsilon^2\omega}{1+r\sigma_\varepsilon^2} > 0 \tag{84}$$

It follows that for the difference to become negative, a needs to be sufficiently small. As we assumed that $a > \frac{(1+r\sigma_\varepsilon^2)\omega}{1+2\psi}$ below, we derive a necessary condition for $\Delta E[\Pi_{iii}] < 0$ assuming $a \to a^{min} = \frac{(1+r\sigma_\varepsilon^2)\omega}{1+2\psi}$. Inserting a^{min} into (81) and solving for ω we get

$$\omega > \sqrt{\frac{2\sigma_\varepsilon^2\psi(1+r\sigma_\varepsilon^2)}{1-2\sigma_\varepsilon^2 r(1+\psi+r\sigma_\varepsilon^2)}}. \tag{85}$$

It follows that $E[\Pi^{**}]$ can possibly exceed $E[\Pi^*]$ only if ω is sufficiently large and $r\sigma_\varepsilon^2$ and ψ are sufficiently low. Conversely, $\Delta E[\Pi_{iii}] > 0$ always holds true if (85) is violated.

■

Proof of Proposition 4

Note that

$$Var[m^{**}] = Var[e^{**} + \varepsilon] = Var[\varepsilon] = \sigma_\varepsilon^2 \tag{86}$$

and

$$Var[m'] = Var[e' + \varepsilon] = Var[\varepsilon] = \sigma_\varepsilon^2. \tag{87}$$

Further

$$Var[y^{**}] = Var[e^{**} + \varepsilon + \delta^{**}] = Var[\varepsilon - \frac{\omega - 2\varepsilon\psi}{1+2\psi}] = Var[\frac{\varepsilon}{1+2\psi}] = \frac{\sigma_\varepsilon^2}{(1+2\psi)^2} \tag{88}$$

and

$$\begin{aligned} Var[y'] &= Var[e' + \varepsilon + \delta'] \\ &= Var[\varepsilon - \frac{-a(1+2\psi) - 2\varepsilon\psi(2+2\psi+r\sigma_\varepsilon^2) + \omega(1+r\sigma_\varepsilon^2)}{(1+2\psi)(2+2\psi+r\sigma_\varepsilon^2)}] \\ &= Var[\varepsilon - \frac{2\varepsilon\psi}{1+2\psi}] = Var[\frac{\varepsilon}{1+2\psi}] = \frac{\sigma_\varepsilon^2}{(1+2\psi)^2}. \end{aligned} \tag{89}$$

■

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Otto von Guericke University Magdeburg
Faculty of Economics and Management
P.O. Box 4120 | 39016 Magdeburg | Germany

Tel.: +49 (0) 3 91 / 67-1 85 84
Fax: +49 (0) 3 91 / 67-1 21 20

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