Expert Decision-Making: A Markovian Approach to Studying the Agency Problem

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Abstract

In this paper, we study the agency problem in an organisation within a Markovian framework. More specifically, the paper presents the case of a principal imposing an incentive-control structure upon an agent to force him to follow the principal's interests for which he was hired, against the tendency of the agent to follow his own interests. Findings point toward the principal's difficulty in controlling the behaviour of the agent through incentives and monitoring; instead, best results are obtained when hiring agents who care for their reputation and refrain from unprofessional behaviours. The implication is that if we consider that it might be difficult to identify this characteristic at the time of the agent's hiring, the best criterion will be to look for low levels of greed in the agent. This conclusion goes in some way against current practices of looking for aggressive agents for the generation of higher profits. Nevertheless, it should be noted that these potential benefits might actually fade away if the agent follows his own interests, instead of the principal's. Another interesting result points to the restricted, although necessary, role of monitoring to control the agent's behaviour, a result that goes against current research interests on measures of corporate governance. The paper is a contribution to expert decision-making.

Keywords: Agency theory, principal-agent, Markov, incentive-control structure, greed, reputation, expert decision-making

1. Introduction

The principal-agent problem arises when the owner (also known as the principal or the shareholder) of an organisation is not the real manager of the entity. Hence, the principal delegates someone (i.e., the agent) to manage the organisation, paying for the service rendered (Jensen & Meckling, 1976). The reasons for such delegation are diverse, but may involve the cost associated with managing the organisation by oneself or not having sufficient knowledge to manage the organisation's performance, there may be a misalignment between the principal's interests and the agent's interests: the principal's interests are the firm performance and profit, and the agent's interests may only be related to receiving the payment from the principal for the service rendered. This misalignment of interests further leads to a conflict of interests between the principal and the agent (Fama & Jensen, 1983b; Jensen & Meckling, 1976).

This problem can generally be solved via a simple contract, through which the principal promises payments to the agent that are precisely the valuation of the agent's performance less some fixed constant, known as the "franchise fee", which is paid by the agent for the right to work for the principal (Sappington, 1991). However, this solution is feasible only if certain assumptions are met (such as the symmetry of precontractual beliefs, or the presumed risk neutrality of the agent). Changes in these assumptions make the contract not to be the optimal solution. There are, however, particular solutions for every issue; for example, when the agent is risk-averse, the solution might be the purchase of an insurance contract (Pauly, 1974; Sappington, 1991).

Mainstream research on agency has been developed along two strands, which are generally referred to as the "principal-agent theory" and the "positive theory of agency" (Eisenhardt, 1989; Jensen, 1983). The former is more mathematics-intensive and non-empirical in its orientation and is focused on explaining that principals are risk-neutral and profit seekers, while agents are risk-averse and rent seekers (Panda & Leepsa, 2017). Early works in this stream are those by Ross (1973), Harris & Raviv (1978), and Holmstrom (1979). The latter is generally non-mathematical and more empirical in its orientation and explains the causes of the agency problem and the cost involved (Panda & Leepsa, 2017). The works by Jensen & Meckling (1976), Fama & Jensen (1983a), and Fama & Jensen (1983b) are among the examples in this second stream.

The positive theory of agency has been criticised on various grounds, but mostly because it focuses primarily on the principal-agent relationship and the cost incurred due to it: the solution is driven only by the principal, regardless of the agent's costs (Pepper & Gore, 2012; Sanders & Carpenter, 2003; Wiseman & Gomez-Mejia, 1998). To address such matters, the above-mentioned authors proposed the behavioural agency theory, which focuses on the association between the agency cost, the agent's performance, his/her personal characteristics (the agent as the boundedly rational, anti-risk/loss taker, who trades off between internal and external benefits), and his/her motivation to pursue the principal's interests. In line with the behavioural agency theory, the present paper will model two characteristics of the agent: greed and reputation.

The literature on the principal-agent theory that considers the agent's greed is scarce and underdeveloped. Wang & Murnighan (2011), for example, studied the main features of greed, and advanced that the neglect of greed in contemporary research is partly due to the "enormous difficulties that surround the seemingly simple task of defining greed" (p. 282). Nevertheless, research works have recently started to appear. In their paper, Pepper et al. (2015), building upon Fehr & Schmidt (1999)'s model of fairness, found that, in some circumstances, "greed" may have to be substituted for "guilt". Furthermore, following Wang and Murnighan's discussion, Haynes et al. (2017) explored to a greater extent the differences between greed and other similar terms (particularly, "self-interest"). Moreover, the authors found that greed had a negative relationship with shareholder returns, but that this relationship was moderated by the presence of a powerful, independent board, managerial discretion, and CEO tenure. In the case of reputation, Ely & Välimäki (2003) constructed a model wherein the long-run agent's concern for reputation resulted in the loss of all surplus. Furthermore, their findings indicated that it is only when agents and principals share the same long-run interests, that such losses can be avoided.

The strategies of the principal generally consist in giving a portion of the profit to the agent and in allocating another portion for the monitoring of the agent. In this case, both the principal's and the agent's interests are aligned: more effort leads to more profit for both parties (Grossman & Hart, 1983). Research shows, however, that this incentive for agents could be counterproductive (e.g., Bénabou & Tirole, 2003; Gneezy et al., 2011). While it is generally acknowledged that monitoring costs help to motivate the agent to increase his effort to fulfill the principal's interests (i.e., increase the profit of the organization), just like with incentives, the action of monitoring the agent could result in the reduction of the agent's performance (Falk & Kosfeld, 2006). Dickinson & Villeval (2008), for example, conducted controlled laboratory experiments whose results showed that many principals engage in costly monitoring, and most agents react to the disciplining effect of monitoring by increasing effort; but the opposite can also happen when monitoring is above a certain threshold.

To see all of these dynamics, in this paper, we use a Markovian framework. A review of the existing literature on Markovian models and agency theory indicates that research efforts have mainly focused on the agent's hidden actions (Plambeck & Zenios, 2000) and hidden information (Zhang & Zenios, 2008), under a traditional or standard agency theory, which focuses on monitoring costs and incentive alignment. In the present paper, we approach the agency problem in a novel way, by modelling the agent's characteristics and the principal's actions under a Markovian framework.

It should be noted that our work differs from studies that approach the agency problem using a Markovian model under a game theory setup. In this study, we use the Markovian framework explicitly, and not just as a subsidiary model under a game theory approach. This direct Markovian approach allows us to reach more refined and detailed conclusions, in contrast to the dichotomous conclusions usually reached under a game theory modelling (characterised by on and off type solutions). Under our approach, we found different regions of behaviour for the principal-agent behaviour: some regions with a very well defined type of behaviour, others with a non-defined type of behaviour, and some regions with oscillating behaviours. Our work enables a more realistic, holistic, and flexible approach to modelling the interaction of the parties. We reach very important results in terms of optimal principal behaviour in accordance with specific actions taken by the agent under a classical game theory approach. In other words, instead of a game theory approach that focuses on how to respond to particular actions taken by the other party, we focus on actions to be taken in view of the personal characteristics of the agent.

Since Markovian frameworks can be designed to model many real-world problems, they have been used widely across a variety of fields and applications, ranging from credit risk management (Siu et al., 2007), credit risk modelling (Georgiou et al., 2021), optimal consumption-investment (Azevedo et al., 2014), and optimal consumption problem (Savku & Weber, 2018) to post-event systems recovery (Dhulipala et al., 2021), the study of citations in academic journals (Delbianco et al., 2020), music composition (Herremans et al., 2015), the study of the impact of incentive schemes and personality-tradeoffs on two-agent coopetition (Chión et al., 2018), risk and reward management in innovation portfolios (Chión & Charles, 2018), the study of the impact of emotions in social media on the stock market in the context of market crashes (Ge et al., 2020) and the analysis of time-oriented emotional patterns (Shao et al., 2019), and traffic behaviour (Chión & Charles, 2019), just to name a few. For a survey of applications of Markov decision processes and their classification according to the use of real-life data, structural results, and computational schemes, the interested readers are referred to the study by White (1993); for Markov chain models and applications, readers can consult Trivedi et al. (2015).

This study offers several theoretical, methodological, and managerial contributions. Theoretically, it demonstrates links between the principal's actions (e.g., compensation and monitoring) and both the agent's personal characteristics (e.g., greed and reputation) and the reward for the organisation. From a methodological point of view, to the best our knowledge, this study is the first to approach the agency problem by modelling the agent's characteristics and the principal's actions under a Markovian framework. The study demonstrates the principal's difficulty in controlling the agent's behaviour through incentives and monitoring; instead, best results are obtained when hiring agents who care for their reputation and refrain from unprofessional behaviours. This is meaningful since prior research (e.g., Dickinson & Villeval, 2008) showed that the monitoring cost increases the agent's performance only when within a certain interval; in all other cases, monitoring could lead to undesirable results. Managerially, the results support the argument that monitoring plays a restricted (although necessary) role in controlling the agent, which goes against current research on measures of corporate governance. Also, the results emphasise the need for managers to look for low level of greed when hiring agents, which also goes against current business practices of hiring aggressive agents to generate maximum profits for the organisation.

The remainder of this paper is organised as follows. After this introduction, we discuss the fundamental theoretical framework by describing the modelling setting and the Markovian model in detail. We then provide a numerical simulation, followed by an extended discussion of the results obtained. We conclude the paper with the study's contributions to the literature and expert systems, managerial implications, and

avenues for future research.

2. The Setting

Let an organisation be composed of two entities: a Principal (\mathbf{P}) , who owns the organisation, and an Agent (\mathbf{A}) , who is hired by \mathbf{P} . \mathbf{P} employs \mathbf{A} to implement actions in accordance with his objectives, but cannot control the actual actions that \mathbf{A} will implement. The organisation can be in one of two states, either in S_1 or in S_2 , as shown in Figure 1. In S_1 , the actions of \mathbf{A} are aligned with the objectives of \mathbf{P} ; by contrast, in S_2 , the actions of \mathbf{A} are aligned with his own interests, which are in conflict with the interests of \mathbf{P} .



Figure 1: The Markovian Process.

Consider \mathbf{R} as the reward per period that can be generated by \mathbf{A} for \mathbf{P} . If the organisation is in state S_1 , $\mathbf{R} > 0$; in S_2 , the reward per period for the organisation is $\mathbf{R} = 0$. In S_2 , wherein \mathbf{A} follows his own interests, he generates for himself a reward equivalent to a fraction β of 1. This β represents the level of greed of \mathbf{A} . This definition is in accordance with Childs (2000), Kirchgassner (2014), and Jin & Zhou (2011). More specifically, we differentiate between self-interest and greed, by modelling the first one as a state S_2 and the second one as a parameter β . To foster state S_1 , \mathbf{P} has to incentivise \mathbf{A} to follow his interests, and to this aim, \mathbf{P} compensates \mathbf{A} with a fraction δ of \mathbf{R} . This compensation is part of the contract and it is supposed to facilitate the alignment between the agent's and the principal's interests (Jensen & Meckling, 1976).

As stated, A was hired to implement actions in accordance with the objectives of P, but these objectives are in conflict with his own objectives. The situation of P is aggravated by not having a natural observability and controllability over the actions taken by A. P has to invest in monitoring to detect and control A's behaviour. As stated by Jensen & Meckling (1976), incurring this cost helps to limit the activities undertaken by A. The efficacy of the monitoring measures is not perfect: these measures are helpful to force a change in A's behaviour towards P's objectives, in order to produce a transition from S_2 to S_1 ; nevertheless, they are ineffective in constraining A to follow P's objectives. These measures involve controls over A, information requirements, particular organisational structures, measures of corporate governance, and so on. These measures translate in a cost of a fraction γ of 1. Forced to change his actions toward P's objectives, A incurs a cost equivalent to a fraction δ of one unit, represented by the recognition of errors, bad performance, managerial hubris, risky behaviour, moral hazard, and so on.

In S_1 , the final reward \mathbf{R} for \mathbf{P} is given by a natural reward of one unit, which is positively affected by \mathbf{A} 'a greed and negatively affected by the monitoring cost and compensation of \mathbf{A} . Thus, it is assumed that the reward for the organisation is impacted positively by \mathbf{A} 's personal characteristic of greed. The monitoring cost comprises both monetary and non-monetary costs; the non-monetary costs are given by the costs of inefficiency introduced by red tape and bureaucracy, among others. Specifically, in S_1 , we have:

Natural reward:	1
Monitoring costs subtraction:	γ
Net natural reward after monitoring cost:	$1-\gamma$
\boldsymbol{A} 's greed effect:	$(1+eta)(1-\gamma)$
Compensation subtraction:	$\alpha(1+\beta)(1-\gamma)$
Reward in S_1 :	$(1+\beta)(1-\gamma) - \alpha(1+\beta)(1-\gamma) = (1+\beta)(1-\gamma)(1-\alpha)$

Thus, two reward matrices can be distinguished:

Reward matrix for A:

$$\boldsymbol{V} = \begin{bmatrix} v_{11} & v_{12} \\ v_{21} & v_{22} \end{bmatrix} = \begin{bmatrix} (1+\beta)(1-\gamma)\alpha & 0 \\ -\delta & \beta \end{bmatrix}.$$
(1)

Reward v_{11} represents the compensation for \boldsymbol{A} for remaining in S_1 , and it is a fraction α of reward $(1 + \beta)(1 - \gamma)$, where β is the level of greed and γ is the amount invested in monitoring. In S_2 , \boldsymbol{A} obtains a reward of $v_{22} = \beta$ for following his own interests. The transition from S_2 to S_1 corresponds to \boldsymbol{A} returning to a professional behaviour, which represents a negative benefit for \boldsymbol{A} of δ due to the loss of image and reputation.

Reward matrix for P:

$$\boldsymbol{W} = \begin{bmatrix} w_{11} & w_{12} \\ w_{21} & w_{22} \end{bmatrix} = \begin{bmatrix} (1+\beta)(1-\gamma)(1-\alpha) & 0 \\ 0 & -\gamma \end{bmatrix}.$$
 (2)

In S_1 , the organisation obtains a reward of $(1 - \gamma)$ minus the cost of compensation and is affected positively by **A**'s greed; thus, $w_{11} = (1 + \beta)(1 - \gamma)(1 - \alpha)$. In S_2 , $\mathbf{R} = 0$ and the cost to be incurred by P is γ , generating $w_{22} = -\gamma$.

On the other hand, the state transition probabilities are defined as follows:

Transition from S_1 to S_2 :

A abandons the professional behaviour in pursuit of his own interests. This probability depends positively on A's reward for following his own interests, β ; and impacts negatively on both the compensation α for following a professional behaviour and on A's appreciation for his reputation δ . Specifically, this probability is assumed to be:

$$p_{12} = \beta(1-\alpha)(1-\delta),\tag{3}$$

with

$$\frac{\partial p_{12}}{\partial \alpha} = -\beta(1-\delta) \le 0 \quad , \quad \frac{\partial p_{12}}{\partial \beta} = (1-\alpha)(1-\delta) \ge 0, \quad \text{and} \quad \frac{\partial p_{12}}{\partial \delta} = -\beta(1-\alpha) \le 0.$$

Thus, p_{12} decreases with the compensation α and increases with **A**'s personal incentive, being negatively affected by the cost faced by **A** for being caught having an unprofessional behaviour.

Transition from S_1 to S_1 :

This transition corresponds to A maintaining a professional behaviour and is defined as a complement to the former probability, p_{12} :

$$p_{11} = 1 - \beta (1 - \alpha)(1 - \delta). \tag{4}$$

Here, we have:

$$\frac{\partial p_{11}}{\partial \alpha} = \beta(1-\delta) \ge 0, \quad \frac{\partial p_{11}}{\partial \beta} = -(1-\alpha)(1-\delta) \le 0, \quad \text{and} \quad \frac{\partial p_{11}}{\partial \delta} = \beta(1-\alpha) > 0.$$

This probability is affected positively by the incentive α , negatively by \mathbf{A} 's personal interests β , and positively by the cost for being caught displaying an unprofessional behaviour.

Transition from S_2 to S_2 :

A persists in an unprofessional behaviour, pursuing his own interests, against P's interests. We assume that this probability is negatively affected by the monitoring measures. Specifically:

$$p_{22} = (1 - \gamma).$$
 (5)

No investment in monitoring, i.e., $\gamma = 0$, would imply $p_{22} = 1$; in other words, A's unprofessional behaviour will not be detected, and A will not have any incentive to change his behaviour, and so the system will remain forever in S_2 , which will be a trapping state. Below, we will rule out this degenerative situation, assuming there is always some investment in some kind of monitoring, i.e., $\gamma > 0$.

Transition from S_2 to S_1 :

The return of A to a professional behaviour is defined by the complement to the former probability, p_{22} :

$$p_{21} = \gamma. \tag{6}$$

Returning to a professional behaviour depends positively on the level of controls imposed on him.

2.1 The Markovian Model

The Markovian model is defined by Figure 1, the reward matrices V and W, and the following transition matrix T:

$$\boldsymbol{T} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} = \begin{bmatrix} (1-\beta)(1-\alpha)(1-\delta) & \beta(1-\alpha)(1-\delta) \\ \gamma & 1-\gamma \end{bmatrix},\tag{7}$$

where α, β, δ , and γ are in the interval (0, 1).

These restrictions correspond to the interpretations of the probabilities for α, β, δ , and γ . In addition, these probabilities rule out uninteresting degenerative cases of the Markovian system, for example, the case of eventually remaining in only one state, or alternating between the two states, or two disconnecting states.

Notice that in the model, two parameters identify P, i.e., α and γ , and two parameters identify A, i.e., β and δ . P has control over his parameters and A is described by his parameters. We use the following nomenclature for these parameters in the model:

- α : Compensation parameter, under the control of **P**.
- γ : Monitoring parameter, under the control of **P**.
- β : Greed parameter, a personal characteristic of A.
- δ : Reputation parameter, a personal characteristic of A.

Asymptotically, the behaviour of the system is described by the left eigenvector associated with the unitary eigenvalue of the transition matrix, T. Hence:

$$\pi_1 = \frac{1 - p_{22}}{1 - p_{22} + p_{12}} \tag{8}$$

and

$$\pi_2 = \frac{p_{12}}{1 - p_{22} + p_{12}}.\tag{9}$$

By replacing the respective values, we have:

$$\pi_1 = \frac{\gamma}{\gamma + \beta(1 - \alpha)(1 - \delta)} \tag{10}$$

and

$$\pi_2 = \frac{\beta(1-\alpha)(1-\delta)}{\gamma+\beta(1-\alpha)(1-\delta)}.$$
(11)

Strictly speaking, these limiting state probabilities indicate the asymptotic frequencies of the organisation being in state S_1 or S_2 ; or equivalently, the probability of finding A pursuing either P's objectives or his own interests, after a large enough number of transitions. Nevertheless, this is a quite restricted interpretation of these probabilities; we can generalise the interpretations of π_1 and π_2 to being indicators of A's effort, dedication, interest, and so on, to pursue P's interests or his own interests, respectively.

On the other hand, the expected transition reward for **A** is given by $q^T = [q_1, q_2]$, where:

$$q_1 = p_{11}v_{11} + p_{12}v_{12} = \left[1 - \beta(1 - \alpha)(1 - \delta)\right](1 + \beta)(1 - \gamma)\alpha \tag{12}$$

and

$$q_2 = p_{21}v_{21} + p_{22}v_{22} = -\gamma\delta + (1-\gamma)\beta,\tag{13}$$

where q_1 represents the expected reward of the next transition, if A is currently in S_1 ; and similarly for q_2 .

The gain for \mathbf{A} is $g = \pi^T q$, where $\pi^T = [\pi_1, \pi_2]$; hence, $g = \pi_1 q_1 + \pi_2 q_2$. By incorporating equations (12) and (13), we further obtain:

$$g = \frac{\gamma}{\gamma + \beta(1-\alpha)(1-\delta)} \left[1 - \beta(1-\alpha)(1-\delta)\right] (1+\beta)(1-\gamma)\alpha + \cdots \\ \frac{\beta(1-\alpha)(1-\delta)}{\gamma + \beta(1-\alpha)(1-\delta)} \left[-\gamma\delta + (1-\gamma)\beta\right],$$
(14)

which is the expected reward per transition for A under an asymptotic behaviour.

Similarly, the expected reward of the transition for \boldsymbol{P} is $h^T = [h_1, h_2]$, where:

$$h_1 = p_{11}w_{11} + p_{12}w_{12} = [1 - \beta(1 - \alpha)(1 - \delta)](1 + \beta)(1 - \gamma)(1 - \alpha)$$
(15)

and

$$h_2 = p_{21}w_{21} + p_{22}w_{22} = -(1-\gamma)\gamma, \tag{16}$$

where h_1 represents the expected reward of the next transition, if **P** is currently in S_1 ; and similarly for h_2 .

The gain for \boldsymbol{P} is $z = \pi^T h$, where $\pi^T = [\pi_1, \pi_2]$; hence, $z = \pi_1 h_1 + \pi_2 h_2$. By incorporating equations (15) and (16), we further obtain:

$$z = \frac{\gamma}{\gamma + \beta(1-\alpha)(1-\delta)} \left[1 - \beta(1-\alpha)(1-\delta)\right] (1+\beta)(1-\gamma)(1-\alpha) - \cdots \\ \frac{\beta(1-\alpha)(1-\delta)}{\gamma + \beta(1-\alpha)(1-\delta)} \left[(1-\gamma)\gamma\right],$$
(17)

which is the expected reward per transition for P under an asymptotic behaviour.

3. Analysis

Our main interest is to analyse the incentive-control structure to be implemented by P on A to realign A's objectives closer to P 's objectives. This structure has a positive reward represented by an incentive parameter α and the monitoring measures on A are represented by a control parameter γ . This structure has to influence the behaviour of A, whose personal characteristics are given by a greed parameter β and a reputation parameter δ .

Notice that the characteristics of \boldsymbol{A} are fixed, i.e., for a specific \boldsymbol{A} there is a specific pair (β, δ) . The gain for \boldsymbol{A} is dependent on both this pair and on the incentive-control structure imposed by \boldsymbol{P} . For each type of \boldsymbol{A} , i.e., for each (β, δ) , \boldsymbol{P} will impose an incentive-control structure to maximise his gain, $z = z(\beta, \delta, \alpha, \gamma)$. Let $(\alpha, \gamma) = (\alpha^* = \alpha^*(\beta, \delta), \gamma^* = \gamma^*(\beta, \delta))$ be the pair that maximises \boldsymbol{P} 's gain, for a specific pair $(\beta, \delta) : z^* = z^*(\beta, \delta, \alpha^*, \gamma^*) \ge z(\beta, \delta, \alpha, \gamma)$, for any pair (α, γ) .

Obviously, α^* and γ^* are functions of β and δ ; $\alpha^* = \alpha^*(\beta, \delta)$ and $\gamma^* = \gamma^*(\beta, \delta)$. After finding the optimal values α^* and γ^* for each pair (β, δ) , the values for $\pi_1^* = \pi_1^*(\beta, \delta, \alpha^*, \gamma^*)$, $\pi_2^* = \pi_2^*(\beta, \delta, \alpha^*, \gamma^*)$, $g^* = g^*(\beta, \delta, \alpha^*, \gamma^*)$, and $z^* = z^*(\beta, \delta, \alpha^*, \gamma^*)$ can be obtained. Based on all these figures, the analysis of the situation can be carried out.

Numerical simulations were performed for the following values of the parameters:

- Greed parameter β : From 0.1 to 0.9, with discrete intervals of 0.1.
- Compensation parameter α : From 0.0 to 0.9, with discrete intervals of 0.1.
- Monitoring parameter γ : From 0.1 to 0.9, with discrete intervals of 0.1.
- Reputation parameter δ : From 0.0 to 0.9, with discrete intervals of 0.1.

Results are shown in Table 1.

3.1 General Analysis: An Overview

In general, we have a situation in which P is trying to define his relationship with A, so as to incentivise A to align his actions in accordance with P's objectives. This is represented in our model as P trying to retain A in S_1 , countering the tendency of A to move to S_2 via incentives and monitoring. In this endeavour, P has to consider the personal characteristics of A, defined by his greed and reputation: (β, δ) . Greed has a positive effect on the rewards for P, but a negative effect on A's pursuit of his own interests, i.e., the attraction of A towards S_2 ; reputation always plays in favour of P.

The actions taken by P, in general, have direct and indirect effects on him, as well as on the entire situation. The direct effects have an impact on the reward matrices of both A and P, that is, V and W; on the other hand, the indirect effects have an impact on these rewards through their influence on the transition matrix, T.

We analyse the situation from the point of view of P, whose problem is to specify the parameters under his control, (α, γ) , so as to maximise his gain; this depends on both his reward matrix, W, and the transition matrix, T. Before we proceed with the specifics, let us view the problem in the context of the parameters that describe it.

Compensation parameter α

It has a direct negative impact on P's reward and is represented by a payment from P to A, as shown by w_{11} . Indirectly, it also has a positive impact on the reward, due to its effect of making state S_1 attractive to A, increasing p_{11} and reducing p_{12} .

Monitoring parameter γ

It has a direct negative impact on \mathbf{P} 's reward, both reducing the reward in S_1 and representing a cost, as shown by w_{11} and w_{22} , respectively. The reduction in w_{11} is a result of the inefficiencies created by the bureaucratic effects due to control systems. Indirectly, the monitoring system has an impact on \mathbf{P} 's reward through its effect on the transition probabilities p_{21} and p_{22} from the transition matrix, \mathbf{T} . This indirect positive effect is a result of the pressures put on \mathbf{A} to abandon his unprofessional behaviour.

Greed parameter β

A's greed has important direct and indirect effects. The direct effect on A's reward is positive in net terms. This personal characteristic of A impacts positively on the reward generated in S_1 , as shown by w_{11} . Indirectly, it affects negatively, pushing A to pursue his own interests, as shown by its negative effect on p_{11} and positive effect on p_{12} .

Table 1: Parameter Values under an Optimal Incentive-Control Structure $(\alpha - \gamma)(\#)$

β	δ	α^*	γ^*	π_1^*	π_2^*	$g^*(\#\#)$	z^*	β	δ	α^*	γ^*	π_1^*	π_2^*	$g^{*}(\#\#)$	z^*
0.10	0.00	0.00	0.20	0.66670	0.33330	0.02670	0.47470	0.60	0.00	0.60	0.30	0.5556	0.4444	0.4704	0.0958
0.10	0.10	0.00	0.20	0.68970	0.31030	0.01860	0.50260	0.60	0.10	0.60	0.30	0.5814	0.4186	0.4696	0.1163
0.10	0.20	0.00	0.20	0.71430	0.28570	0.01140	0.53260	0.60	0.20	0.50	0.30	0.5556	0.4444	0.3964	0.1431
0.10	0.30	0.00	0.20	0.74070	0.25930	0.00520	0.56470	0.60	0.30	0.40	0.30	0.5435	0.4565	0.3328	0.1773
0.10	0.40	0.00	0.20	0.76920	0.23080	0.00000	0.59940	0.60	0.40	0.30	0.30	0.5435	0.4565	0.2735	0.2228
0.10	0.50	0.00	0.20	0.80000	0.20000	-0.00400	0.63680	0.60	0.50	0.10	0.30	0.5263	0.4737	0.1709	0.2878
0.10	0.60	0.00	0.20	0.83330	0.16670	-0.00670	0.67730	0.60	0.60	0.00	0.30	0.5556	0.4444	0.1067	0.3796
0.10	0.70	0.00	0.20	0.86960	0.13040	-0.00780	0.72140	0.60	0.70	0.00	0.30	0.6250	0.3750	0.0788	0.4953
0.10	0.80	0.00	0.10	0.83330	0.16670	0.00170	0.79350	0.60	0.80	0.00	0.20	0.6250	0.3750	0.1200	0.6440
0.10	0.90	0.00	0.10	0.90910	0.09090	0.00000	0.88280	0.60	0.90	0.00	0.20	0.7692	0.2308	0.0692	0.8886
0.20	0.00	0.00	0.30	0.60000	0.40000	0.05600	0.31920	0.70	0.00	0.70	0.30	0.5882	0.4118	0.5889	0.0794
0.20	0.10	0.00	0.30	0.62500	0.37500	0.04130	0.35180	0.70	0.10	0.60	0.30	0.5435	0.4565	0.5003	0.0976
0.20	0.20	0.00	0.30	0.65220	0.34780	0.02780	0.38710	0.70	0.20	0.60	0.30	0.5725	0.4275	0.5010	0.1217
0.20	0.30	0.00	0.30	0.68180	0.31820	0.01590	0.42570	0.70	0.30	0.50	0.30	0.5505	0.4495	0.4271	0.1529
0.20	0.40	0.00	0.20	0.62500	0.37500	0.03000	0.46800	0.70	0.40	0.40	0.30	0.5435	0.4565	0.3624	0.1944
0.20	0.50	0.00	0.20	0.66670	0.33330	0.02000	0.52270	0.70	0.50	0.20	0.30	0.5172	0.4828	0.2528	0.2532
0.20	0.60	0.00	0.20	0.71430	0.28570	0.01140	0.58510	0.70	0.60	0.00	0.30	0.5172	0.4828	0.1497	0.3418
0.20	0.70	0.00	0.20	0.76920	0.23080	0.00460	0.65720	0.70	0.70	0.00	0.30	0.5882	0.4118	0.1153	0.4665
0.20	0.80	0.00	0.20	0.83330	0.16670	0.00000	0.74130	0.70	0.80	0.00	0.30	0.6818	0.3182	0.0795	0.6310
0.20	0.90	0.00	0.10	0.83330	0.16670	0.01500	0.86700	0.70	0.90	0.00	0.20	0.7407	0.2593	0.0985	0.8954
0.30	0.00	0.10	0.30	0.52630	0.47370	0.13440	0.21520	0.80	0.00	0.70	0.30	0.5556	0.4444	0.6213	0.0663
0.30	0.10	0.00	0.30	0.52630	0.47370	0.08530	0.25020	0.80	0.10	0.70	0.30	0.5814	0.4186	0.6239	0.0844
0.30	0.20	0.00	0.30	0.55560	0.44440	0.06670	0.29090	0.80	0.20	0.60	0.30	0.5396	0.4604	0.5337	0.1056
0.30	0.30	0.00	0.30	0.58820	0.41180	0.04940	0.33640	0.80	0.30	0.60	0.30	0.5725	0.4275	0.5368	0.1341
0.30	0.40	0.00	0.30	0.62500	0.37500	0.03380	0.38760	0.80	0.40	0.50	0.30	0.5556	0.4444	0.4616	0.1727
0.30	0.50	0.00	0.30	0.66670	0.33330	0.02000	0.44570	0.80	0.50	0.30	0.30	0.5172	0.4828	0.3387	0.2271
0.30	0.60	0.00	0.20	0.62500	0.37500	0.04500	0.51200	0.80	0.60	0.10	0.30	0.5102	0.4898	0.2319	0.3091
0.30	0.70	0.00	0.20	0.68970	0.31030	0.03100	0.60300	0.80	0.70	0.00	0.30	0.5556	0.4444	0.1556	0.4387
0.30	0.80	0.00	0.20	0.76920	0.23080	0.01850	0.71510	0.80	0.80	0.00	0.30	0.6522	0.3478	0.1113	0.6172
0.30	0.90	0.00	0.20	0.86960	0.13040	0.00780	0.85630	0.80	0.90	0.00	0.20	0.7143	0.2857	0.1314	0.9006
0.40	0.00	0.40	0.30	0.55560	0.44440	0.29000	0.15490	0.90	0.00	0.80	0.30	0.6250	0.3750	0.7816	0.0576
0.40	0.10	0.30	0.30	0.54350	0.45650	0.23360	0.18300	0.90	0.10	0.70	0.30	0.5525	0.4475	0.6579	0.0729
0.40	0.20	0.20	0.30	0.53960	0.46040	0.18000	0.21800	0.90	0.20	0.70	0.30	0.5814	0.4186	0.6630	0.0940
0.40	0.30	0.00	0.30	0.51720	0.48280	0.09170	0.26360	0.90	0.30	0.60	0.30	0.5435	0.4565	0.5709	0.1204
0.40	0.40	0.00	0.30	0.55560	0.44440	0.07110	0.32040	0.90	0.40	0.50	0.30	0.5263	0.4737	0.4971	0.1560
0.40	0.50	0.00	0.30	0.60000	0.40000	0.05200	0.38640	0.90	0.50	0.40	0.30	0.5263	0.4737	0.4318	0.2071
0.40	0.60	0.00	0.30	0.65220	0.34780	0.03480	0.46380	0.90	0.60	0.20	0.30	0.5102	0.4898	0.3170	0.2837
0.40	0.70	0.00	0.20	0.62500	0.37500	0.06750	0.55600	0.90	0.70	0.00	0.30	0.5263	0.4737	0.1989	0.4115
0.40	0.80	0.00	0.20	0.71430	0.28570	0.04570	0.69030	0.90	0.80	0.00	0.30	0.6250	0.3750	0.1463	0.6029
0.40	0.90	0.00	0.20	0.83330	0.16670	0.02330	0.86930	0.90	0.90	0.00	0.20	0.6897	0.3103	0.1676	0.9043
0.50	0.00	0.50	0.30	0.54550	0.45450	0.37390	0.11930								
0.50	0.10	0.40	0.30	0.52630	0.47370	0.31290	0.14260								
0.50	0.20	0.40	0.30	0.55560	0.44440	0.30620	0.17270								
0.50	0.30	0.20	0.30	0.51720	0.48280	0.20370	0.21140								
0.50	0.40	0.10	0.30	0.52630	0.47370	0.14930	0.26360								
0.50	0.50	0.00	0.30	0.54550	0.45450	0.09090	0.33410								
0.50	0.60	0.00	0.30	0.60000	0.40000	0.06800	0.42000								
0.50	0.70	0.00	0.30	0.66670	0.33330	0.04670	0.52500								
0.50	0.80	0.00	0.20	0.66670	0.33330	0.08000	0.66670								
0.50	0.90	0.00	0.20	0.80000	0.20000	0.04400	0.88000								

Note. (#) Four combinations of (β, δ) had two optimal solutions (α^*, γ^*) : (0.2, 0.4), (0.3, 0.6), (0.4, 0.7), and (0.6, 0.8); thus, each pair of solutions for these four combinations had the same optimal z, the solution with the highest g was considered in each pair. (##) Notice that, strictly speaking, g^* cannot be negative, as A always has the option not to make any transition into S_2 , in which case $g = \alpha(1-\gamma)(1+\beta)$. The negative values shown in the table are due to the fact that the model does not consider the decisions of A, but rather the general policy behaviours represented by the parameters β and δ that characterise A. In the table, the negative values of g^* correspond to the cases wherein $\alpha = 0$, and thus, the gain of A should have been 0 (the figures shown in the table are quite close to this null figure, which actually shows that this policy behaviour represents Awell). This situation has no effect on the results and analysis presented in this research, and it is just a simplification to make the model simpler.

Reputation parameter δ

It has a positive indirect effect on P, restraining the unprofessional behaviour of A, as can be seen from the transition matrix, which shows a positive effect on p_{11} and a negative effect on p_{12} .

All these direct and indirect effects have multiple interactions among them, impacting on the asymptotic gains of both P and A, making direct conclusions difficult to reach, and requiring a careful and systematic analysis of the results obtained. The final results are shown in Table 1, which we have to analyse in more detail to derive better insights on the problem.

3.2 Specific Analysis

Tables 2, 3, 4, and 5 structure the results from Table 1 for further analysis. All these tables are double-entry tables, with the two parameters that describe A as entries: β defines rows and δ columns. The next sections are dedicated to analysing these results.

3.2.1 Analysis of results: Optimal incentive-control structure

$\beta \downarrow \delta \rightarrow$	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Mean
0.1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.1000	0.1000	0.1800
0.2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.3000	0.3000	0.3000	0.3000	0.2000	0.2000	0.2000	0.2000	0.2000	0.1000	0.2300
0.3	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0100
	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.2000	0.2000	0.2000	0.2000	0.2600
0.4	0.4000	0.3000	0.2000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0900
	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.2000	0.2000	0.2000	0.2700
0.5	0.5000	0.4000	0.4000	0.2000	0.1000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1600
	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.2000	0.2000	0.2800
0.6	0.6000	0.6000	0.5000	0.4000	0.3000	0.1000	0.0000	0.0000	0.0000	0.0000	0.2500
	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.2000	0.2000	0.2800
0.7	0.7000	0.6000	0.6000	0.5000	0.4000	0.2000	0.0000	0.0000	0.0000	0.0000	0.3000
	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.2000	0.2900
0.8	0.7000	0.7000	0.6000	0.6000	0.5000	0.3000	0.1000	0.0000	0.0000	0.0000	0.3500
	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.2000	0.2900
0.9	0.8000	0.7000	0.7000	0.6000	0.5000	0.4000	0.2000	0.0000	0.0000	0.0000	0.3900
	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.3000	0.2000	0.2900
Mean	0.4222	0.3667	0.3333	0.2556	0.2000	0.1111	0.0333	0.0000	0.0000	0.0000	0.1722
	0.2889	0.2889	0.2889	0.2889	0.2778	0.2778	0.2667	0.2556	0.2222	0.1778	0.2633

Table 2: Optimal Incentive-Control Structure (α^*, γ^*)

Table 2 and Figures 2 and 3 show the optimal incentive-control structure (α^*, γ^*) for each type of agent, identified by the pair (β, δ) . The optimal compensation α^* is increasing with the greed β of \boldsymbol{A} and is decreasing with \boldsymbol{A} 's reputation δ . Greed plays in favour of the rewards for \boldsymbol{P} , but it also means that for a type of agent with higher incentives to pursue his own interests, a higher compensation α is required to attenuate this behaviour. This higher compensation required to contain \boldsymbol{A} 's greed is, nonetheless, attenuated by \boldsymbol{A} 's concern for his reputation.

The optimal monitoring measures, represented by γ^* , show a stable behaviour, varying mainly between 0.2 and 0.3, although some few cases correspond to 0.1. Thus, we have a situation indicating that monitoring is necessary, but its use is restricted by the costs it generates, not only in terms of expenses but also in terms

of loss of efficiency. That monitoring is necessary can be seen in the fact that for all types of agents (β, δ) , γ^* is positive. Although the value of γ^* is relatively uniform, there is a slightly increasing tendency with greed, also a slightly decreasing tendency with reputation. These small tendencies in the same direction of compensation show a slight complementary effect between both the parameters.



Figure 2: Optimal incentive-control structure: α^* .

Though, in general, there is a restricted, but necessary, need for monitoring, this plays an important function for the cases of low greed ($\beta \leq 0.3$) and high levels of reputation ($\delta \geq 0.7$); in these cases, monitoring is enough to have an optimal policy for \boldsymbol{P} , allowing him not to use compensation for \boldsymbol{A} .



Figure 3: Optimal incentive-control structure: γ^* .

3.3.2 Analysis of results: Limiting state probabilities under an optimal incentive-control structure

Table 2 and Figure 4 show the behaviour of the limiting state probabilities under an optimal incentivecontrol structure for P. As stated above, these limiting state probabilities should be taken more generally than simple probabilities of staying in one of the two possible states; they should be understood as the relative weights of the attitudes, efforts, and interests of A to pursue the interests of P, relative to his own interests.

$\beta\downarrow\delta\rightarrow$	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Mean
0.1	0.6667	0.6897	0.7143	0.7407	0.7692	0.8000	0.8333	0.8696	0.8333	0.9091	0.7826
	0.3333	0.3103	0.2857	0.2593	0.2308	0.2000	0.1667	0.1304	0.1667	0.0909	0.2174
0.2	0.6000	0.6250	0.6522	0.6818	0.6250	0.6667	0.7143	0.7692	0.8333	0.8333	0.7001
	0.4000	0.3750	0.3478	0.3182	0.3750	0.3333	0.2857	0.2308	0.1667	0.1667	0.2999
0.3	0.5263	0.5263	0.5556	0.5882	0.6250	0.6667	0.6250	0.6897	0.7692	0.8696	0.6442
	0.4737	0.4737	0.4444	0.4118	0.3750	0.3333	0.3750	0.3103	0.2308	0.1304	0.3558
0.4	0.5556	0.5435	0.5396	0.5172	0.5556	0.6000	0.6522	0.6250	0.7143	0.8333	0.6136
	0.4444	0.4565	0.4604	0.4828	0.4444	0.4000	0.3478	0.3750	0.2857	0.1667	0.3864
0.5	0.5455	0.5263	0.5556	0.5172	0.5263	0.5455	0.6000	0.6667	0.6667	0.8000	0.5950
	0.4545	0.4737	0.4444	0.4828	0.4737	0.4545	0.4000	0.3333	0.3333	0.2000	0.4050
0.6	0.5556	0.5814	0.5556	0.5435	0.5435	0.5263	0.5556	0.6250	0.6250	0.7692	0.5881
	0.4444	0.4186	0.4444	0.4565	0.4565	0.4737	0.4444	0.3750	0.3750	0.2308	0.4119
0.7	0.5882	0.5435	0.5725	0.5505	0.5435	0.5172	0.5172	0.5882	0.6818	0.7407	0.5843
	0.4118	0.4565	0.4275	0.4495	0.4565	0.4828	0.4828	0.4118	0.3182	0.2593	0.4157
0.8	0.5556	0.5814	0.5396	0.5725	0.5556	0.5172	0.5102	0.5556	0.6522	0.7143	0.5754
	0.4444	0.4186	0.4604	0.4275	0.4444	0.4828	0.4898	0.4444	0.3478	0.2857	0.4246
0.9	0.6250	0.5525	0.5814	0.5435	0.5263	0.5263	0.5102	0.5263	0.6250	0.6897	0.5706
	0.3750	0.4475	0.4186	0.4565	0.4737	0.4737	0.4898	0.4737	0.3750	0.3103	0.4294
Mean	0.5798	0.5744	0.5851	0.5839	0.5855	0.5962	0.6131	0.6572	0.7112	0.7955	0.6282
	0.4202	0.4256	0.4149	0.4161	0.4145	0.4038	0.3869	0.3428	0.2888	0.2045	0.3718

Table 3: Limiting State Probabilities under an Optimal Incentive-Control Structure (π_1^*, π_2^*)

Under the optimal incentive-control structure, Table 3 and Figure 4 show a predominance of S_1 , wherein A displays a professional behaviour, i.e., π_1^* is always greater than 0.5 and reaches values as high as over 0.9. Nevertheless, the behaviour of π_1^* is not independent of the type of agent (β, δ) . There is a decreasing trend in the behaviour of π_1^* with respect to greed, up to some level of critical greed; from there onwards, the behaviour of this limiting state probability starts oscillating. This critical level of greed increases with the level of reputation. The decreasing trend of the behaviour with respect to greed corresponds to A's higher inclination towards his own interests, in accordance with his level of greed; but this behaviour changes from that critical level onwards with the increasing importance that compensation acquires with greed, as seen above. The increasing trend in the behaviour of α^* counterbalances the greedy behaviour, producing an oscillating behavior of π_1^* . The critical value of β increases as reputation increases, and this increase in the critical value of β produces a lower value of critical α (as seen above).

On the other hand, the reputation characteristic of A shows a somewhat similar behaviour to greed. For low values of greed, ($\beta \leq 0.3$), π_1^* shows a decreasing trend in behaviour with respect to reputation. For greater values of greed, we appreciate a first interval with a minor oscillating behaviour of π_1^* , up to some level of critical reputation, and from there onwards, π_1^* shows a clearly increasing trend in behaviour with respect to reputation. This critical level of reputation increases with the level of greed. The oscillating behaviour is explained by the same reasons given for the behaviour of π_1^* with respect to greed in the previous paragraph.



Figure 4: Limiting state probabilities under an optimal incentive-control structure: π_1^* .

The higher levels of π_1^* correspond to agents with low greed and high reputation. In general, this situation favours P, although it has to be validated or qualified through the levels of gains registered with this type of agents.

In general, in light of the observations made, greed plays a restricted negative effect against π_1^* , and reputation plays a more definitive role in favour of it.

3.2.3 Analysis of results: Gains under an optimal incentive-control structure

For P, the gains depend on A's greed and the capacity to retain him in S_1 ; it is also negatively affected by the costs of monitoring and compensation. The gains for A depend on the gains for P and on A following his own interests. Under an optimal incentive-control structure, Table 4 and Figures 5 and 6 show the gains, i.e., g^* and z^* , generated for A and P, respectively.

For low values of greed ($\beta \leq 0.3$), \mathbf{P} 's gain is higher than \mathbf{A} 's gain, and the same occurs for high levels of reputation ($\delta \geq 0.7$). For high values of greed and low values of reputation, we have mixed results. This relative behaviour responds to the null compensation α^* for low greed, also to the high levels of reputation; as well as, to the relatively high values of the limiting state probabilities for being in state S_1 . The situation is mixed for the cases with high greed and low reputation, and this is mainly due to the mixture of the different effects produced by greed: benefiting \mathbf{P} 's and \mathbf{A} 's rewards, imposing higher costs of compensation to \mathbf{P} , and increasing the probability of being in S_2 .

$\beta\downarrow\delta\rightarrow$	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Mean
0.1	0.0267	0.0186	0.0114	0.0052	0.0000	-0.0040	-0.0067	-0.0078	0.0017	0.0000	0.0045
	0.4747	0.5026	0.5326	0.5647	0.5994	0.6368	0.6773	0.7214	0.7935	0.8828	0.6386
0.2	0.0560	0.0413	0.0278	0.0159	0.0300	0.0200	0.0114	0.0046	0.0000	0.0150	0.0222
	0.3192	0.3518	0.3871	0.4257	0.4680	0.5227	0.5851	0.6572	0.7413	0.8670	0.5325
0.3	0.1344	0.0853	0.0667	0.0494	0.0338	0.0200	0.0450	0.0310	0.0185	0.0078	0.0492
	0.2152	0.2502	0.2909	0.3364	0.3876	0.4457	0.5120	0.6030	0.7151	0.8563	0.4612
0.4	0.2900	0.2336	0.1800	0.0917	0.0711	0.0520	0.0348	0.0675	0.0457	0.0233	0.1090
	0.1549	0.1830	0.2180	0.2636	0.3204	0.3864	0.4638	0.5560	0.6903	0.8693	0.4106
0.5	0.3739	0.3129	0.3062	0.2037	0.1493	0.0909	0.0680	0.0467	0.0800	0.0440	0.1676
	0.1193	0.1426	0.1727	0.2114	0.2636	0.3341	0.4200	0.5250	0.6667	0.8800	0.3735
0.6	0.4704	0.4696	0.3964	0.3328	0.2735	0.1709	0.1067	0.0788	0.1200	0.0692	0.2488
	0.0958	0.1163	0.1431	0.1773	0.2228	0.2878	0.3796	0.4953	0.6440	0.8886	0.3451
0.7	0.5889	0.5003	0.5010	0.4271	0.3624	0.2528	0.1497	0.1153	0.0795	0.0985	0.3075
	0.0794	0.0976	0.1217	0.1529	0.1944	0.2532	0.3418	0.4665	0.6310	0.8954	0.3234
0.8	0.6213	0.6239	0.5337	0.5368	0.4616	0.3387	0.2319	0.1556	0.1113	0.1314	0.3746
	0.0663	0.0844	0.1056	0.1341	0.1727	0.2271	0.3091	0.4387	0.6172	0.9006	0.3056
0.9	0.7816	0.6579	0.6630	0.5709	0.4971	0.4318	0.3170	0.1989	0.1463	0.1676	0.4432
	0.0576	0.0729	0.0940	0.1204	0.1560	0.2071	0.2837	0.4115	0.6029	0.9043	0.2910
Mean	0.3714	0.3270	0.2985	0.2482	0.2088	0.1526	0.1064	0.0767	0.0670	0.0619	0.1918
	0.1758	0.2001	0.2295	0.2652	0.3094	0.3668	0.4414	0.5416	0.6780	0.8827	0.4091

Table 4: Gains under an Optimal Incentive-Control Structure (g^*, z^*)

We have been referring to the relative behaviour of A and P. With respect to the absolute behaviour of A, in general, we appreciate that his gains increase with greed and decrease with reputation, a situation which clearly corresponds to the benefits reported for a greedy behaviour and the cost in terms of the loss of reputation associated with a greedy behaviour. With respect to P, in general, we appreciate decreasing gains with respect to A's greed for low and medium values of reputation ($\delta \leq 0.6$). For high values of reputation ($\delta \geq 0.7$), in general, we observe a decreasing gain for P with greed, except for the extreme case of $\delta = 0.9$. In this extreme case, z^* is decreasing with greed up to some level, and from there onwards, P's gain starts increasing, which corresponds to the benefit in the reward generated by A's greedy behaviour, the null compensation payment, and the restricted effect of greed on A due to him caring for his reputation.



Figure 5: Gains under an optimal incentive-control structure: g^* .

In Table 4 and respective figures, we can appreciate that, in general, for P, the characteristic of A that favours him is A's high reputation, which is almost independent of greed. This signals P's limitations in

controlling A's greed through compensation and monitoring. For low or intermediate levels of reputation, the characteristic of A that is more convenient to P is the low greed. Table 5 and Figures 7 and 8 show the behaviour of the total gains H and the participation of P in these total gains¹. In general, we distinguish between four types of agents:

- Type I: Low greed and low reputation ($\beta \leq 0.3$ and $\delta \leq 0.6$).
- Type II: High greed and low reputation ($\beta \ge 0.4$ and $\delta \le 0.6$).
- Type III: Low greed and high reputation ($\beta \leq 0.3$ and $\delta \geq 0.7$).
- Type IV: High greed and high reputation ($\beta \ge 0.4$ and $\delta \ge 0.7$).



Figure 6: Gains under an optimal incentive-control structure: z^* .

Type I is characterised by total gains that are decreasing with greed and increasing with reputation. The same behaviour is observed in the participation of P in these total gains. This type of agents show a professional behaviour, concentrating on pursuing P's interests; they do not require compensation and almost all gains are accrued by P. The negative side for P of this type of agents is that A's low greed affects the generation of higher rewards.

¹There are some participations over 100% due to the negative gains for A, which are explained in a note to Table 1.

$\beta \downarrow c$	$\delta \rightarrow$	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	Mean
0.	.1	0.5013	0.5212	0.5440	0.5699	0.5994	0.6328	0.6707	0.7136	0.7952	0.8828	0.6431
		94.7%	96.4%	97.9%	99.1%	100%	100.6%	101%	101.1%	99.8%	100%	99.1%
0.	.2	0.3752	0.3930	0.4150	0.4416	0.4980	0.5427	0.5966	0.6618	0.7413	0.8820	0.5547
		85.1%	89.5%	93.3%	96.4%	94.0%	96.3%	98.1%	99.3%	100%	98.3%	95%
0.	.3	0.3496	0.3354	0.3576	0.3858	0.4214	0.4657	0.5570	0.6341	0.7335	0.8642	0.5104
		61.5%	74.6%	81.4%	87.2%	92.0%	95.7%	91.9%	95.1%	97.5%	99.1%	87.6%
0.	.4	0.4449	0.4167	0.3980	0.3553	0.3916	0.4384	0.4986	0.6235	0.7360	0.8927	0.5196
		34.8%	43.9%	54.8%	74.2%	81.8%	88.1%	93.0%	89.2%	93.8%	97.4%	75.1%
0.	.5	0.4932	0.4555	0.4789	0.4152	0.4129	0.4250	0.4880	0.5717	0.7467	0.9240	0.5411
		24.2%	31.3%	36.1%	50.9%	63.8%	78.6%	86.1%	91.8%	89.3%	95.2%	64.7%
0.	.6	0.5662	0.5859	0.5396	0.5101	0.4964	0.4587	0.4862	0.5740	0.7640	0.9578	0.5939
		16.9%	19.9%	26.5%	34.8%	44.9%	62.7%	78.1%	86.3%	84.3%	92.8%	54.7%
0.	.7	0.6683	0.5979	0.6227	0.5800	0.5568	0.5059	0.4914	0.5818	0.7105	0.9939	0.6309
		11.9%	16.3%	19.5%	26.4%	34.9%	50%	69.5%	80.2%	88.8%	90.1%	48.8%
0.	.8	0.6876	0.7083	0.6393	0.6709	0.6342	0.5658	0.5410	0.5942	0.7285	1.0320	0.6802
		9.6%	11.9%	16.5%	20%	27.2%	40.1%	57.1%	73.8%	84.7%	87.3%	42.8%
0.	.9	0.8391	0.7308	0.7569	0.6913	0.6531	0.6389	0.6007	0.6105	0.7491	1.0719	0.7342
		6.9%	10%	12.4%	17.4%	23.9%	32.4%	47.2%	67.4%	80.5%	84.4%	38.2%
Me	ean	0.5473	0.5272	0.5280	0.5134	0.5182	0.5193	0.5478	0.6184	0.7450	0.9446	0.6009
		38.4%	43.8%	48.7%	56.3%	62.5%	71.6%	80.2%	87.1%	91.0%	93.8%	67.3%

Table 5: Total Gains and Composition under an Optimal Incentive-Control Structure $(H^* = g^* + z^*, z^*/H^*)$

Type II, in general, is characterised by total gains that are increasing with greed and decreasing with reputation. With this type of agents, the optimal incentive-control structure enters in operation to attenuate A's greed and to control it through compensation and monitoring. The costs of the control system that has to be imposed on A have an important effect on the participation of P in the total gains. The participation of P becomes lower than that of A. Reputation affects negatively the total gains because it refrains the generation of rewards by A in the pursuit of his own interests. This type of agents exhibit a relatively unprofessional behaviour.



Figure 7: Total gains and composition under an optimal incentive-control structure: H^* .

Type III is characterised by total gains that are relatively stable with respect to greed and increasing with reputation. The increasing behaviour of the gains with reputation corresponds to the low costs due to reputation and monitoring for remaining mainly in S_1 , and thus, not incurring in costs associated with w_{22}^*

and p_{21}^* . A shows a high professional behaviour in favour of P, who obtains almost all gains.

Type IV is characterised by a relatively similar behavior to the behaviour of Type III, i.e., total gains that are increasing with respect to both greed and reputation. A's behaviour, although still professional (in the sense that it is aligned with the interests of P), is at a slightly lower level of professionalism than in Type III, due to the higher level of greed; this can be observed through some loss in P's participation in the total gains.

Clearly, the preferred types of agents for P are I, III, and IV. What is surprising is the preference for low levels of greed, as shown by types I and III, which goes against the generation of rewards in S_1 , but signals the difficulty in controlling greed as working against P. The best way to restrain greed playing against P is through reputation, but this is a personal characteristic of A, that can only be controlled by P when hiring A. Type II is the worst type of agent for P, wherein greed is difficult to control and is unrestrained by reputation in this category of agents.



Figure 8: Total gains and composition under an optimal incentive-control structure: z^*/H^* .

3.3. Summary of Results

Table 6 summarises the results, consolidating the information from Tables 2 to 5 for the 90 types of agents (90 pairs of (β, δ) classified in the four types defined previously). To this end, the mean and standard deviation² values of the main variables are presented for agent types I, II, III, and IV. The following can be appreciated:

3.3.1 High-reputation agents: Type III and Type IV

These types of agents generate higher total gains (H^*) when compared to agents type I and II; moreover, more than 85% of these higher total gains will mainly go to **P**. With these types of agents, the organisation remains mainly in S_1 , as can be seen from the values of 0.8196 and 0.6722 for π_1^* , for Type III and Type

 $^{^{2}}$ The standard deviation values are presented only for the reader's personal reference to the variability involved in each variable.

IV, respectively.

These are explained by the agents' concern for their own reputation. The high concern for reputation refrains the agents from displaying an unprofessional behaviour, remaining mainly in S_1 by own decision; this allows \boldsymbol{P} to recognise null compensation (α^*) and slightly lower investment in monitoring (γ^*), relative to the respective cases of low reputation (Types I and II). Minimising these costs allows \boldsymbol{P} to accrue almost entirely the total gains (H^*). In addition, the total gains increase when the costs of loss of reputation and of monitoring are minimised, given that the system remains mainly in S_1 .

$\beta\downarrow$	$\delta \rightarrow$	Low		High	
		Mean	\mathbf{SD}	Mean	\mathbf{SD}
Low	α^*	0.0048	0.0005	0	0
	γ^*	0.2476	0.0025	0.1667	0.0022
	π_1^*	0.6615	0.0065	0.8196	0.0039
	π_2^*	0.3385	0.0065	0.1804	0.0039
	g^*	0.0328	0.0010	0.0079	0.0001
	z^*	0.4517	0.0156	0.7597	0.0084
	H^*	0.4845	0.0096	0.7676	0.0078
	z^*/H^*	91.70%	0.0088	98.90%	0.0003
High	α^*	0.3667	0.0627	0	0
	γ^*	0.3	0	0.2444	0.0025
	π_1^*	0.5517	0.0009	0.6722	0.0062
	π_2^*	0.4483	0.0009	0.3278	0.0062
	g^*	0.3507	0.0376	0.0989	0.0022
	z^*	0.2002	0.0106	0.6713	0.0293
	H^*	0.5509	0.0125	0.7702	0.0268
	z^*/H^*	40.20%	0.0614	86.50%	0.0054

Table 6: Optimal Incentive-Control Structure: Summary of Results

Note. SD - Standard deviation; β low range 0.1 - 0.3 and high range 0.4 - 0.9; δ low range 0.0 - 0.6 and high range 0.7 - 0.9.

The difference between agent types III and IV is greed. Greed has two opposing effects on the gains of P; it generates a higher reward in S_1 , but there will be a higher tendency for A to pursue his own interests. From Table 6, it can be appreciated that, in the context of high-reputation agents, the positive effect for Pdoes not compensate the negative effect: z^* is higher for Type III relative to Type IV. Thus, greed plays against P for high-reputation agents, though it plays slightly in favour of the total gains: H^* is greater for Type IV relative to Type III.

3.3.2 Low-reputation agents: Type I and Type II

These cases show much lower total gains, H^* , when compared to the cases of the higher-reputation agents. This is explained by the elevation of A's unprofessional behaviour, who now has lower constraints for reputation; the limiting state probability for S_2 is much higher, relative to the cases of the high-reputation agents. This situation increases the cost of reputation for A and the cost of monitoring for P.

Although the total gains are reduced, the gains for A improve considerably relatively to A's high reputation, as can be seen by means of comparing Type I with Type III and Type II with Type IV. By contrast, Preduces his gains to a great extent, when compared to the cases of the high-reputation agents, as can be seen by comparing the respective cases. Also, the low concern for reputation increases the limiting state probabilities of S_2 , in relation to the respective cases of the high-reputation agents. The differences between the two cases of low-reputation agents are explained by greed, and these are great. Higher greed favours A, against P. Type II, which corresponds to high greed, is the only case wherein the gains for A are bigger than the gains for P. Also, Type II is the only case wherein the combination of high greed and low reputation forces P to invest significantly in compensation α^* and in monitoring to contain A's greed. All of this affects P's gains; the reduction in total gains is attenuated by the gains registered by A in the pursuit of his own interests.

3.3.3 Low greed versus high greed: Cases I and II relative to III and IV, respectively

High greed favours total gains, relative to low greed (Type II relative to I, and IV to III), indicating that the benefits generated by greed in the reward in S_1 more than compensate the higher cost implied by the higher limiting probabilities in S_2 . The higher limiting probabilities in S_2 generate higher costs in terms of loss of reputation and monitoring.

High greed also generates higher gains for A relative to low greed, as can be seen in g^* , when comparing Type II with I, and Type IV with III. This difference is generated by the higher tendency of A to follow his own interests, obtaining the respective rewards. By contrast, for P, low greed generates higher gains than high greed does, which is explained by the lower costs of compensation and monitoring.

Among the four types of agents, only Type II generates more significant gains for A, while at the same time, P achieves his lowest gains. Thus, greed and low concern for reputation play in favour of A and against P. By contrast, Type III, corresponding to low greed and high reputation, plays in favour of P, generating his best result.

High reputation plays largely in favour of P, but it can be difficult to identify this characteristic at the moment of hiring A; were this the case, P should guide his hiring decision based on A's level of greed, trying to select a low-greed-type-of-agent. This result signals the difficulty and the cost of refraining agents from pursuing the interest of P, which forces the agents to renounce at their aggressiveness to pursue rewards for the organisation in state S_1 . This result conflicts with what is common practice in current business, but it is ratified by known cases of problems generated by agents working in their own interests against P' interests.

4. Contributions and Implications for Practice

This paper has studied the agency problem in an organisation in a novel way, by modelling the agent's characteristics and the principal's actions under a Markovian framework, which is a methodological contribution. It presented the case of a principal imposing an incentive-control structure on an agent to force him to follow the principal's interests, for which he was hired, against the tendency to follow his own interests, which are in opposition with the principal's objectives. The agent is characterised by his greed and concern for reputation (pair (β, δ)), and the principal is seen as selecting optimal levels for compensation and monitoring on the agent, selecting the pair (α, γ) . An interesting characteristic of the model is that the reward for the organisation, for the principal, is affected positively by the level of the agent's greed, but at the same time, this greed affects negatively the principal's interests through the higher tendency of the agent to pursue his own interests.

Theoretically, the paper demonstrated links between the principal's actions (e.g., compensation and monitoring) and both the agent's personal characteristics (e.g., greed and reputation) and the reward for the organisation. The main conclusion refers to the principal's difficulty in controlling the agent's behaviour through incentives and monitoring. This difficulty is reflected in the characteristics of the optimal measures to be taken by the principal on the agent: emphasising a low level of greed, even going against the generation of higher rewards for the organisation, so as to minimise the possibility of the agent to follow an unprofessional behaviour, against the principal's interests. However, the effect of incentives on motivation should be considered more deeply. Several authors argued that incentives could mislead intrinsic and extrinsic motivation (Bénabou & Tirole, 2003; Gneezy et al., 2011). Another feature is that we are not considering the case of the hidden cost of control (Falk & Kosfeld, 2006) in monitoring cost. As Dickinson & Villeval (2008) remarked, only within a certain interval, the monitoring cost increases the agent's performance; in all the others, monitoring could lead to undesirable results.

The complexity in controlling the agent's behaviour is also seen in that the best results for the principal are generated when hiring high-reputation-oriented agents, i.e., agents who are concerned about their reputation and refrain from displaying an unprofessional behaviour. Thus, the best results for the principal actually depend on the agent's personal characteristics. If we consider that it might be difficult to identify this characteristic of high reputation at the moment of the hiring of the agent, the best policy will be to emphasise low greed. For example, research has shown that potential candidates who during their interviews express lofty aspirations for profits or resources are more likely to be judged as greedy and acquisitive (Helzer & Rosenzweig, 2020). In this sense, then, from a real-world motivation perspective, recruitment teams should include experts able to assess whether an agent's propensity for greed is excessive or not. This is even more important in the context in which "the question of how people gauge excess in the context of resource-pursuit is psychologically rich" (Helzer & Rosenzweig, 2020, p. 113), which makes it difficult for a recruiter to achieve a full understanding of the mental threshold beyond which resource pursuit is seen as excessive without proper training.

Managerially, this main conclusion to emphasise low greed in the agent, in some way goes against current business practices of looking for aggressive agents for the generation of higher profits for the organisation. These potential benefits could fade away if the agent follows his own interests, instead of the principal's interests, a tendency which is reinforced by his own greed, as exemplified by many famous cases in business. Another interesting managerial result also refers to the restricted, although necessary, role of monitoring to control the agent, a result that goes against current research interests on measures of corporate governance. This restricted role is explained by the inefficiency generated by bureaucracy, red tape, and so on, which are involved in any monitoring system.

In terms of contributions to and implications for expert systems, our results may be particularly useful for an efficient human resource management, which has been acknowledged in the literature as being a very complicated endeavour (Otero & Otero, 2012). Human Resources are always in need of "accurate assessment and representation of available competences as well as effective mapping of required competences for specific jobs and positions" (Bohlouli et al., 2017, p. 83), as these are widely regarded as essential tools to enhance organisational competitiveness (Lee, 2010). In this sense, the findings of the present study can inform and be incorporated, for example, into a Web-based application, such as an expert system for recruitment, that can aid Human Resources and other relevant expert decision-makers in determining the best candidate for a specific job.

5. Conclusions and Avenues for Future Research

Although the analysis in this paper is theoretical, it has allowed us to reach the important conclusion that the traditional incentive-control system exercised by the principal, while still necessary, plays a limited role in controlling the agent's behaviour. Instead, the emphasis should be placed on the agent's personal characteristics. Future research efforts should be directed toward the refinement of the relationship between the agent's greed and the organisation's rewards; also, toward the assessment of the monitoring effects on the organisation's rewards. Another line of research should point toward designing more elaborate Markovian frameworks, considering a better characterisation of the agent and of the incentive-control system, as well as other possible system states not considered in this paper. Finally, empirical studies should be dedicated to testing the acceptance or rejection of the results presented in this research. In this sense, it would be interesting to extend this research with a study that assesses the robustness of the results found by means of supporting the proposed theoretical framework with real data.

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