Original article

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Performance-based pay and limited information access

An agent-based model of the hidden action problem

Abstract: Models involving human decision-makers often include idealized assumptions, such as rationality, perfect foresight, and access to relevant information. These assumptions usually assure the models' internal validity but, at the same time, might limit the models' power to explain empirical phenomena. This paper addresses the well-known model of the hidden action problem, which proposes an optimal performance-based sharing rule for situations in which a principal assigns a task to an agent and the task outcome is shared between the two parties. The principal cannot observe the action taken by the agent to carry out this task. We introduce an agent-based version of this problem in which we relax some of the idealized assumptions. In the proposed model, the principal and the agent only have limited information access and are endowed with the ability to gain, store and retrieve information from their (finite) memory. We follow an evolutionary approach and analyze how the principal's and the agent's decisions affect their respective utilities, the sharing rule, and task performance over time. The results suggest that the optimal (or a close-to-optimal) sharing rule does not necessarily emerge in all cases. The results indicate that the principal's utility is relatively robust to variations in memory. On the contrary, the agent's utility is significantly affected by limitations in the principal's memory, whereas the agent's memory appears to only have a minor effect.

Keywords: robustness, replication, limited rationality, agent-based modeling, simulation

JEL: M20, C63, D00

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1 Introduction

In the history of research on behavioral control, the concept of rational expectations emerged as the dominant paradigm (Muth 1961), which went hand in hand with the extensive development of sophisticated mathematical methods and models with sometimes idealized assumptions about individuals. Up to today, such approaches have played an essential role in many fields, such as management and economics. Most of these models assume agents who are rational in their behavior, employ sophisticated optimization methods, usually possess all (or at least most) pieces of information to come up with optimal solutions immediately, and mostly make no errors in doing so (Thaler 2000; Farmer and Foley 2009). However, it has already been recognized that technically correct and valid models often lack the power to explain empirical phenomena (Franco et al. 2020) and calls to include behavioral insights from other disciplines—such as cognitive psychology—have emerged (Royston 2013; Hämäläinen, Luoma, and Saarinen 2013; Leitner and Behrens 2015a; Wall and Leitner 2021; Wall, Chen, and Leitner 2024). Franco and Hämäläinen (2016) point out that increased attention to behavioral aspects becomes prominent whenever scientific fields reach maturity and argue that, amongst others, this is the case in economics, accounting, and strategic management.

We place our research in the stream of research that analyzes the robustness of economic models to relaxations of the included and often restrictive assumptions. In particular, in our research we focus on the assumptions of information availability (and limitations thereof) in the well-known model of the hidden action problem introduced by Holmström (1979). This model is based on a principal who assigns a task to an agent. The agent acts on behalf of the principal by making an effort to carry out the task assigned to him, while the principal's role is to provide capital and incentives. The modeled situation is further characterized by information asymmetry in the form of hidden actions. The principal can only observe the task outcome but not the action taken by the agent, which is why the principal can only employ a performance-based compensation mechanism. The model provides this mechanism by creating a rule to optimally share the task outcome between the principal and the agent (Caillaud and Hermalin 2000; Eisenhardt 1988; Lambert 2001). The assumptions considered in this model include what Axtell (2007) refers to as the economic sweet spot: Rationality, homogeneity, and equilibrium solutions. We are particularly interested in the conditions of rationality that also include issues related to information availability.

Economic models often implicitly follow the idea that decision-makers possess the necessary capabilities to access all relevant pieces of information. Keeping in mind that information can take different forms, such as complex texts, multimedia materials, or information that is gathered by observing the environment, these required capabilities are truly manifold and rich (McCreadie and Rice 1999). This renders the assumptions implicitly included in economic models nontrivial. In a microeconomic context, Leitner, Rausch, and Behrens (2017) and Leitner, Brauneis, and Rausch (2015) analyze the effects of limited information in capital budgeting by modeling overconfident decision-makers, and principals and agents with limited foresight, respectively. In the context of the hidden action problem, Leitner and Wall (2021, 2022) limit the principal's and the agent's respective capabilities to search for the optimal sharing rule. In the vein of this related research, we transfer the hidden action model into an agent-based model (Guerrero and Axtell 2011; Leitner and Behrens 2015a). By doing so, we propose an agent-based model of the hidden action problem with principals and agents who suffer from limitations in information access. We focus on the following questions: *How do limitations in the principal's and the agent's information availability in the context of the hidden action problem affect (i) the rule to share the task outcome between the principal and the agent, (ii) the agent's effort, and (iii) the principal's and the agent's respective utilities.*

To demonstrate that our agent-based model effectively integrates the hidden action model, we first establish that the solutions derived from our model align with those suggested by Holmström (1979) under conditions of unlimited information for both the principal and the agent. When information is restricted, our findings suggest that the allocation of task outcomes between the principal and the agent depends solely on the principal's information. Specifically, greater informational access for the principal leads to an increased share of outcomes for the agent. Moreover, the principal's information predominantly influences the agent's effort; consistent with many economic models, the agent's behavior is driven by the incentives provided. We further observe that the agent's information does not impact the effort exerted.

Regarding utilities, our analysis indicates that the principal's utility remains largely unaffected by his information state, as he can adjust the incentive mechanisms to consistently maximize utility. In contrast, the agent's utility is significantly influenced by environmental volatility and the principal's level of information. This suggests potential scenarios where a risk-neutral principal might withhold a risk premium from a risk-averse agent. Furthermore, since the principal consistently achieves maximum utility, there is minimal incentive to enhance her information state. This leads to scenarios where the agent's dependence on the principal is disproportionately high.

The remainder of this paper is structured as follows: We discuss the relevant background in Sec. 2. Section 3 discusses our approach to limit the principal's and the agent's information availability, formalizes the proposed agent-based model, and introduces the simulation setup. The results are presented in Sec. 4, and Sec. 5 discusses the results. Finally, Sec. 6 concludes the paper.

2 Related work

2.1 Holmström's hidden action model

The hidden action model introduced in Holmström (1979) describes the relationship between one principal who assigns a task to one agent. In particular, the principal designs a contract that includes the task to be carried out and a rule to share the outcome, and offers this contract to the agent. If the agent accepts the contract, he makes an effort (often also referred to as action) to carry out the task assigned to him. Together with an exogenous factor, this action generates the task outcome. At the same time, acting leads to disutility for the agent. The sharing rule included in the contract defines—before the action is taken—how the outcome is to be shared between the principal and the agent. The model presented by Holmström (1979) is a non-repeated model, indicating that it encapsulates a single execution of the specified sequence outlined above. As a result, it does not account for temporal dynamics, including the distribution of effort over several periods, contract re-negotiations, and the implications of present actions on future payoffs (as, for example, done in Ma 1991). The hidden action model introduced in Holmström (1979) is capable of describing relations between one principal and one agent in a wide range of areas, including the relationship between employer and employee, buyer and supplier, and client and contractor (Eisenhardt 1989; Caillaud and Hermalin 2000; Leitner and Wall 2021; Reinwald, Leitner, and Wall 2020).

The sequence of events within the hidden action model is included in Fig. 1, whereby the main features can be summarized as follows: In $\tau = 0$, the principal designs the contract and offers it to the agent who makes his decision about whether or not to accept it in $\tau = 1$. In $\tau = 2$, the agent selects an effort level $a \in \mathbf{A} \subseteq \mathbb{R}$ from a set of effort levels $\mathbf{A}$ that are feasible to carry out the task. The agent's selected effort level a is *hidden* to the principal, i.e., the principal cannot observe it because the costs for observing it are prohibitively high or this information is not accessible to her. Consequently, there is an information asymmetry regarding the effort level in favor of the agent. The exogenous factor $\theta \sim N(\mu, \theta)$ takes effect in $\tau = 3$, and it is a random variable that describes the state of nature, which includes, for example, the behavior of suppliers or customers. The outcome x materializes in $\tau = 4$; it is a function of the agent's effort level a and an exogenous

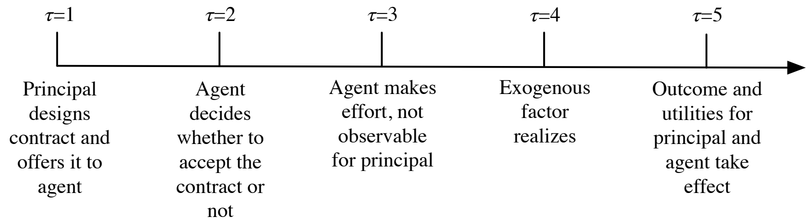

Fig. 1: Sequence of events within Holmström's hidden action model

factor θ and follows the production function $x = x(a, \theta)$. Both the principal and the agent can observe the outcome. There is information asymmetry regarding the exogenous factor: Unlike the principal, the agent can observe the exogenous factor or deduce it from the outcome. If the principal knows of the exogenous factor, she can deduce the agent's effort level from the outcome, which would render the hidden action problem trivial since all information asymmetry would be resolved, and the principal could pay the agent based on his effort. As a consequence of the information asymmetry, the principal can only base the sharing rule on the outcome.

The principal is risk-neutral. Her utility comes from the generated outcome x minus the agent's compensation $s(x)$ so that

$$U_P(x, s(x)) = x - s(x) \ . \tag{1}$$

The agent is risk-averse and characterized by the utility function

$$U_A(s(x), a) = V(s(x)) - G(a) \ , \tag{2}$$

where $V(s(x))$ stands for the utility from his share of the outcome and $G(a)$ indicates the disutility of the effort he makes to carry out the task, with $V' > 0$ and $x_a \geq 0$.[1] Given these characteristics of the hidden action model, the principal's optimization problem to generate the optimal sharing rule is formalized as follows:

$$\max_{s(\cdot),a} E\left(U_P\left(x, s(x)\right)\right) \tag{3a}$$

$$s.t\ E\left(U_A(s(x), a)\right) \geq \bar{U} \tag{3b}$$

$$a \in \arg\max_{a' \in \mathbf{A}} E\left(U_A(s(x), a')\right) \tag{3c}$$

1. The subscript a denotes the partial derivative concerning a.

Equations 3b and 3c are constraints that have to be considered by the principal. In particular, Eq. 3b represents the participation constraint that ensures that the agent gets a minimum utility $\bar{U}$ and therefore accepts the contract. This minimum utility is also called reservation utility and represents the agent's best outside option. Equation 3c is the incentive compatibility constraint and aligns the agent's objective (to maximize his utility) with the principal's objective. This constraint affects the agent's choice of effort level a. The notation 'arg max' represents the set of all arguments that maximizes the objective function that follows. The solution to the problem in Eqs. 3a–3c is provided in Appendix A.

2.2 Related work on extensions to repeated models of the hidden action problem

The hidden action model introduced in Holmström (1979) has been extended in several directions, whereby we are particularly interested in works that extend the model towards a multi-period or repeated model, and this section aims to give an illustrative overview of these extensions. Initial steps towards a model that spans multiple periods are introduced by Rubinstein and Yaari (1983) and Radner (1985), focusing on problems repeated indefinitely with no discounting from both the agent and the principal. They explore how the agent's rewards adapt based on their historical performance, demonstrating that a contract can be formulated to eliminate inefficiencies associated with moral hazard. Conversely, Lambert (1983) proposes a model with a finite horizon, incorporating dynamic production functions and discounting of the principal's and agent's utilities. This model highlights the significance of long-term contracts for addressing moral hazard, by offering the agent a long-term commitment and utilizing their performance history to mitigate uncertainty in their actions. Rogerson (1985) also takes into account discounting from both the principal's and the agent's perspectives, demonstrating that the history of performance is crucial in crafting an optimal contract. Building upon this foundation, Spear and Srivastava (1987) further develop the concept by also introducing a repeated moral hazard model that incorporates discounting. Utilizing this model, they explore how contracts can feasibly incorporate dependency on historical actions and examine the evolution of these contracts over time.

Broadening the analysis, Holmström and Milgrom (1987) propose a continuous time model and investigate instances in which agents are compensated at the end of a finite duration, with Holmström and Milgrom (1991) acknowledging that their findings accurately reflect short-term dynamics. Holmström and Milgrom (1987) demonstrate that contracts adopt a linear format with respect to total output under certain conditions, such as agents with exhibiting exponential utility and the effort entailing monetary costs. This finding has been further explored by researchers like Schättler and Sung (1993), who devise a more general mathematical framework, and Hellwig and Schmidt (2002), who examine the prerequisites for discrete-time models to align with the findings of Holmström and Milgrom (1987). Williams (2015) also extends the model introduced in Holmström and Milgrom (1987). In particular, he is concerned with situations in which the agent has hidden saving, which is why his consumption and wealth cannot be monitored. Sannikov (2008) contributes to this line of research by showing that optimal long-term contracts exhibit complex non-linear wage and effort patterns. They detail the circumstances under which an agent can retire with an optimal contract, where the decision to continue or not at each step is influenced by prospective wages and effort levels.

Edmans and Gabaix (2011) are concerned with fixed contracts in the hidden action context. They reference the work of Grossman and Hart (1992), who demonstrated the complexities arising from fixed contracts in discrete-time scenarios. In response, Edmans and Gabaix (2011) introduce a model featuring contracts that are easier to manage by revising a crucial premise: the agent has the ability to perceive environmental noise prior to exerting effort. They contend that without this modification, agents would behave in a manner aimed at fulfilling expected incentives. Research has also focused on the issue of an agent's decision to stay indefinitely with the principal. While many studies assume such indefinite commitment, there are models that account for limited commitment. A significant amount of this work is aimed at creating contracts that, in any situation, give agents no reason to exit, ensuring the contract's infinite validity (e.g., Thomas and Worrall 1988; Kocherlakota 1996; Phelan 1995). Another approach is followed by Wang and Yang (2019); they address this interaction between the principal and the agent, introducing a model that features stochastic alternatives, dynamic contracts, and a mechanism for endogenous self-enforcement.

There are a number of previous works that focus on uncertainty in information about performance metrics. For instance, Chaigneau, Edmans, and Gottlieb (2014) examine information's role and its constraints concerning performance metrics within hidden action scenarios. They draw on the informativeness principle (Shavell 1979; Holmström 1979), which posits that principals should seek out highly precise performance indicators. Emphasizing this principle, Chaigneau, Edmans, and Gottlieb (2014) highlight the necessity of weighing the informational benefits against the associated costs, a task complicated by the indirect relationship between additional information and contracting problem parameters when deriving optimal contracts proves challenging. Utilizing the moral hazard framework, they introduce a model to scrutinize the benefits principals gain from enhanced information accuracy. MacLeod (2003) takes up the argument provided in Prendergast (1993) who argues that jobs in which objective performance measures are available are very rare, and rather bonuses are often based on subjective performance evaluations. In this vein, MacLeod (2003) explores (one-period) models where performance measures are not always fully accessible or may even be entirely unavailable. In these models, agent evaluations are based more on subjective assessments by the principal. Similarly, Fuchs (2007) argues that certain labor market phenomena, like wage compression and periodic reviews, can serve as effective strategies to mitigate moral hazard on the agent's part, especially when performance evaluations are subjective and held privately.

Some of previous works focused on uncertainty regarding the agent's characteristics. For example, Cohen, Deligkas, and Koren (2022) examine scenarios involving hidden actions, where the principal is unaware of not only the agent's effort but also their utility function and action space. They present a model wherein the principal iteratively discerns the characteristics of an optimal contract by extending offers to identical agents and monitoring the results. Additionally, Cohen, Deligkas, and Koren (2022) introduce a learning algorithm tailored for this purpose. Prat and Jovanovic (2014) focus into hidden action scenarios with long-term contracts, especially when an agent's capabilities of perform tasks remain unknown. They assume the persistence of an agent's capabilities and base their argumentation and the accumulation of information over time to facilitate incentive provision. In a similar vein, Lai, Liu, and Li (2021) address scenarios with unknown agent capabilities, arguing that as the contractual period extends towards infinity, uncertainty diminishes because the agent's capabilities become fully revealed. Conversely, He et al. (2017) and DeMarzo and Sannikov (2016) tackle stochastic uncertainty through learning, proposing models that equate stochastic future profits from output with uncertainty about agent abilities. Mekonnen (2017) builds upon these works, addressing the limited knowledge regarding the production function, which introduces uncertainty about outcome distributions. In his framework, both the principal and the agent form individual beliefs about this distribution, updating their beliefs based on past outcomes while the agent can influence the principal's perceptions. To address these information limitations, Mekonnen (2017) incorporates an additional state variable in computing optimal contracts.

In addition, there is a line of research that employs simulation-based research approaches to assess the robustness of the hidden action model to its included assumptions. Leitner and Wall (2021) modify the hidden action model's assumptions, introducing information uncertainty regarding the environmental variable and the action space. In this adaptation, the principal and the agent are equipped with distinct information systems for data retrieval. This study observes the parameters for incentive mechanisms that emerge at the organizational level. Following this, Leitner and Wall (2022) conduct a detailed examination of the micro-level behavioral dynamics in scenarios characterized by limited information about the action space and environment. Furthering this research, Reinwald, Leitner, and Wall (2022) focus solely on the parties' knowledge of the environmental variable and, extending beyond previous research, consider the memory capacities of both the principal and the agent.

Our research relates to the previous works as follows: Reinwald, Leitner, and Wall (2022) provide an initial analysis of how restricted information access impacts the organizational level. The research effort presented in the following augments this body of work by delivering a comprehensive analysis of the effects of limited information on the environmental variable and constrained memory capacity, both at the macro (organizational) and micro (individual) levels. Our research primarily focuses on how limited access to information impacts the utilities of both the principal and the agent, the premium parameter within the organization's incentive scheme, and overall macro-level performance. This area of interest aligns with the objectives outlined by Spear and Srivastava (1987), who explore how contracts evolve. However, our goal is not to devise an optimal contract accounting for all elements of uncertainty. Instead, we investigate how the mechanism proposed by Holmström (1979) holds up when faced with constraints on the memory capacities of both the principal and the agent. In our model, the intertemporal dynamics manifest as cumulative learning by both parties. Echoing prior research, we account for how performance metrics depend on the agent's historical actions by simulating the agent's time-sequenced, hill-climbing search aimed at optimization with limited information. Consequently, the agent's potential actions in any given period are confined to those in close proximity to the action taken in the preceding period (for details see Sec. 3). We assume both the principal and the agent adopt a short-sighted approach, disregarding the sequence of future rewards and, therefore, exclude any discounting in our model. Furthermore, we proceed under the assumption of certainty regarding both the performance metrics and the agent's characteristics.

2.3 Related work on assumptions in the hidden action model

Previous research notes that many economic models, including the hidden action model and most of the models discussed above, often rely on assumptions regarding the rationality and homogeneity of the involved parties, as well as their pursuit of equilibrium solutions (Axtell 2007). In our research, we specifically investigate the rationality assumption with a particular focus on information availability, aiming to understand to what degree the conclusions drawn from the hidden action model remain valid when this assumption is relaxed.

Expanding the modeling assumptions, including loosening the constraints on rationality, leads to a reduction in mathematical tractability (Latacz-Lohmann and Hamsvoort 1997) and, in particular, to models that cannot be resolved through traditional mathematical methods. Despite these challenges, there is a consensus among researchers on the need for models that more accurately mirror real-world scenarios (Beker 2023; Steele 2023; Leitner and Wall 2021). Interestingly, Gil and Zanarone (2016) highlight the importance of addressing information availability in economic models to foster the development of empirically robust theories, which could lead to a new frontier for *nonstandard* economic theories. A substantial body of research in this area corresponds to the so-called positive branch of research on principal-agent theory. The theoretical branch focuses on the implications of the assumptions embedded in models, including the hidden action model and its extensions discussed above. In contrast, the positive branch primarily addresses the practical applicability and validity of these models. From a methodological standpoint, this branch often employs empirical and conceptual methods (Shapiro 2005; Leitner and Behrens 2015a; Wall and Leitner 2021).

The assumptions explored within the positive branch of principal-agent theory are diverse. For instance, Wright, Mukherji, and Kroll (2001) examine the assumptions surrounding an agent's self-interest and risk attitudes, concluding that insights from behavioral research should be integrated into economic models. Similarly, Wiseman and Gomez-Mejia (1998) study risk preferences and assert that incorporating behavioral research into economic models is a promising research direction. Hendry (2002) extends this discussion, identifying issues beyond opportunism that principals encounter, including incompetence, bounded rationality as described by Simon (1957), and human fallibility. Building on Hendry (2002)'s work, Kauppi and Van Raaij (2015) empirically investigate maverick buying in government agencies, focusing on goal congruence and information asymmetry. Their findings suggest that incompetence often provides significant explanatory power within their model. Additionally, Ferraro, Pfeffer, and Sutton (2005) argue that the assumptions commonly included in economic models often possess a self-fulfilling nature, where theorizing about a phenomenon can cause changes that make the observed reality align more closely with the theoretical predictions.

Within the positive branch, there also exists a specific strand of research dedicated to the accessibility of specific pieces of information. For example, Keser and Willinger (2007) perform laboratory experiments to analyze the agent's behavior in hidden action situations. They are specifically interested in the behavioral consequences of employing the fair-offer theory (see Keser and Willinger 2000) compared to the mechanisms derived from the hidden action model. Hoppe and

Schmitz (2018) also employ experimental methods to study hidden action situations with non-contractible outcomes. They show that relatively lower effort is made when the outcome is non-contractible. Karlan and Zinman (2009) perform a field experiment in a consumer credit market, and they find strong evidence for the existence of moral hazard problems, ultimately resulting in 13% to 21% of default.

Agent-based modeling and simulation are increasingly recognized as a promising research methodology for bridging the gap between the theoretical and positive branches of principal-agent research. Unlike traditional methods that depend on mathematical resolution of models, this approach allows for the conduct of numerical experiments. Through these experiments, researchers can statistically analyze and deduce a model's behavior, offering valuable insights. This is particularly beneficial for addressing models of limited mathematical tractability that arise when the rigid assumptions of traditional models are relaxed.

Significant applications of agent-based modeling have emerged at the interface between theoretical and positive principal-agent research. For instance, Guerrero and Axtell (2011) investigated the implications of various assumptions in a model of firm dynamics. Similarly, Leitner and Behrens (2015b), Leitner, Brauneis, and Rausch (2015), and Leitner, Rausch, and Behrens (2017) have effectively modeled the behaviors of overconfident decision-makers in scenarios of optimal capital allocation. This paper contributes to this line of research by extending the assumptions of the hidden action model to include limitations in information retrieval and recall, which results in restricted information access and affects both the principal's and the agent's understanding of the organizational environment. We base this modelling choice on previous research, such as Giguère and Love (2013), which suggests that limitations in memory retrieval introduce noise into the decision-making process, and McMillan and Overall (2017), who argue that in an organizational context, limited information retrieval and recall are fundamental factors contributing to misaligned capacities and precede complex organizational failures. We believe that extending the hidden action model to incorporate these often-overlooked dimensions may contribute to the development of a more robust theory.

3 Model

3.1 Limiting the principal's and agent's information

We transfer the hidden action model introduced in Sec. 2.1 into an agent-based model, which, amongst others, allows us to include relaxed assumptions about the principal's and the agent's information availability.[2] Doing so allows us to study the robustness of the solution suggested by the formal model in the context of more realistic decision-makers (Guerrero and Axtell 2011; Leitner and Behrens 2015b).

Type of information	**Holmström's model**		**Agent-based model**	
	Principal	**Agent**	**Principal**	**Agent**
Agent's utility function	+	+	+	+
Agent's reservation utility	+	+	+	+
Agent's entire action space	+	+	–	+
Action taken by the agent	–	+	–	+
Production function	+	+	+	+
Observed outcome	+	+	+	+
Realized exogenous factors	–	+	–	+
Estimations of exogenous factors	**n.a.**	**n.a.**	+	–
***True* expected value of exogenous factor**	+	+	–	–
***Learned* expected value of exogenous factor**	**n.a.**	**n.a.**	+	+

\+ indicates information is available
– indicates information is not available
n.a. indicates information is not considered in the model.

Tab. 1: Assumptions regarding main pieces of information available in Holmström's hidden action model and the agent-based model

2. Further key features of our approach are that the researcher can analyze rich institutional arrangements and contingencies, including learning and emergence, and bridge the micro-macro divide. For a review of the advantages and difficulties related to the approach of agent-based computational economics, the reader is referred to Wall and Leitner (2021) and Leitner and Wall (2015). It is important to note that principal-agent models and agent-based models follow two different research paradigms; for further details, see Leitner and Behrens (2015b).

In this paper, we employ the concept of information introduced in Frieden and Hawkins (2010): We denote the information *about a system* by I. In the principal-agent context, I could represent the information available to the principal and the agent. Following the concept of McCreadie and Rice (1999) of information as a good or a commodity, this information can be produced (e.g., by observation), purchased, replicated, passed along, etc. In addition, there is information J, which is the complete information *intrinsic to a system*. Then, any new observation about the system can be modeled as an information flow process $J \to I$. The extent to which individuals are informed about a system can be expressed by the distance $J - I$. In the hidden action model, shared information is part of the information I accessible to both the principal and the agent. In contrast, the agent's private information (e.g., about effort or the environment) is part of the information I for the agent only.

We are interested in exclusively limiting the principal's and the agent's respective information about the environment. In the original hidden action model, both the principal and the agent have full information about the *expected value* of the exogenous factor, and the agent has information about the actual realization of the environment. Put into the context of the information concept introduced above, for the principal and the agent, information about the expected value of the environmental variable is part of the information J, and the distance $J - I$ for this piece of information is equal to zero. Following the logic of the optimization problem introduced in Eqs. 3a–3c, this enables the principal to come up with the optimal sharing rule immediately.

In the agent-based model, we limit the principal's and the agent's respective capabilities so that they no longer possess all relevant capabilities to, for example, gather, process, store, and retrieve information about the environment in the following way:

– We limit the principal's information about the environment. She knows that the exogenous variable follows a Normal Distribution, but due to limited information, she can no longer compute the *true* expected value of the environment. At the same time, we endow her with the ability to *estimate* the exogenous variable after the outcome has materialized and store the estimations in her memory.
– We also limit the agent's information about the environment so that he cannot compute the *true* expected value of the environment either. The agent is also aware of the exogenous variable's distribution. In contrast to the principal, the agent can *observe* the realizations of the exogenous variable, and he can store the observations in his memory.

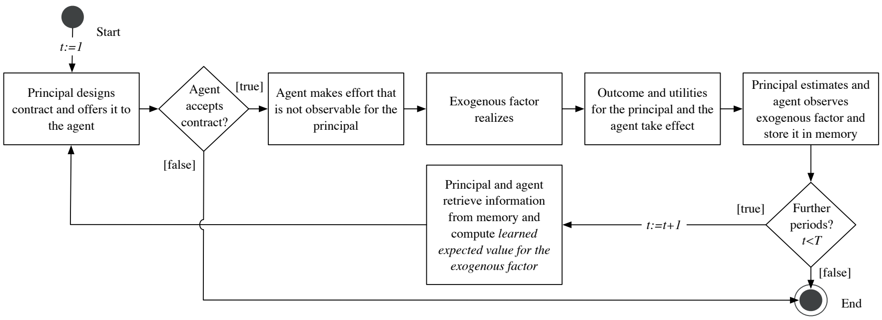

Fig. 2: Sequence of events in the agent-based model

- Since both the principal and the agent learn about the environment (either by observation or estimation), we refer to it as simultaneous and sequential learning.
- The principal's and the agent's memory is limited. Once new information is learned, the principal and the agent replace the oldest information stored in their memory with the latest estimation and observation, respectively.
- Once the information about the exogenous variable is required for decision-making, the principal and the agent retrieve the available information from their memory. They compute the expected value based on the information available to them, which is also interpreted as the *perception* of the environment. We refer to it as the *learned* expected value of the exogenous factor.

The assumptions about information in the hidden action model and the agent-based version thereof are summarized in Tab. 1.

3.2 The agent-based model of the hidden action problem

3.2.1 The principal's and agent's respective utility functions

The hidden action model in Holmström (1979) is a single-period model, and it allows the principal to come up with the optimal sharing rule immediately. In contrast, the agent-based model introduced here is a multi-period model, which includes limitations in the principal's and agent's respective information and a learning mechanism. An overview of the sequence of events within the agent-based model is provided in Fig. 2 We indicate the time steps for the agent-based model by $t = 1, ..., T$.

Description	Notation
Endogenous variables:	
Principal's utility	U_P
Agent's utility	U_A
Timesteps	t
Outcome in t	$x_t = a_t + \theta_t$
Agent's effort in t	a_t
Incited effort in t	$\tilde{a}_t$
Exogenous variable in t	θ_t
Principal's expected outcome for effort level a' **in** t	$\tilde{x}_{Pt}(a')$
Agent's expected outcome for effort level a' **in** t	$\tilde{x}_{At}(a')$
Agent's share of the outcome in t	$s(x_t) = x_t \cdot \rho_t$
Premium parameter included in the contract in t	ρ_t
Premium parameter for effort level a' **in** t	$\rho_t(a')$
Principal's set of all feasible actions in t	$\mathbf{A}_{Pt}$
Principal's candidates for incited effort in t	$\tilde{\mathbf{A}}_{Pt}$
Agent's set of all feasible actions in t	$\mathbf{A}_{At}$
Estimations of the exogenous factors available to the principal in t	$\mathbf{\Theta}_{Pt}$
Observations of the exogenous factors available to the agent in t	$\mathbf{\Theta}_{At}$
Principal's *learned* expectation of the exogenous factor in t	$\tilde{\theta}_{Pt}$
Agent's *learned* expectation of the exogenous factor in t	$\tilde{\theta}_{At}$
Exogenous variables:	
Maximum timesteps	T
Agent's Arrow-Pratt measure of risk-aversion	η
Principal's memory	m_P
Agent's memory	m_A

Tab. 2: Notation for the agent-based model

To account for multiple periods, we reformulate the principal's utility function to

$$U_P(x_t, s(x_t)) = x_t - s(x_t), \tag{4}$$

where x_t and $s(x_t)$ denote the outcome and the agent's share of the outcome in t. The outcome follows the production function

$$x_t = a_t + \theta_t, \tag{5}$$

where $\theta_t \sim N(\mu, \sigma)$ indicates the exogenous factor that takes effect in t, and a_t indicates the agent's effort in t. The sharing rule includes ρ_t, which indicates the premium parameter in t, and is formalized by

$$s(x_t) = x_t \cdot \rho_t \ . \tag{6}$$

The principal can adjust the premium parameter ρ_t in every timestep, i.e., whenever the principal designs a new contract, she has a specific effort level $\tilde{a}_t$ in mind that she wants the agent to make. We refer to $\tilde{a}_t$ as incited effort. In every t, the principal can adapt the premium parameter to incentivize the agent to make this effort. Details on the computation of the incited effort and the premium parameter are provided in Sec. 3.2.3.

The agent's CARA utility function is formalized by

$$U_A(s(x_t), a_t) = \underbrace{\frac{1 - e^{-\eta \cdot s(x_t)}}{\eta}}_{V(s(x_t))} - \underbrace{\frac{a_t^2}{2}}_{G(a_t)}, \tag{7}$$

where η denotes the Arrow-Pratt measure of risk-aversion (Arrow 1973). The notation used in the agent-based model is summarized in Tab. 2.

3.2.2 Simultaneous and sequential learning model

The principal and the agent dispose of an individual memory m_P and m_A, respectively. The higher m_P and m_A, the more estimations and observations of the exogenous factor the principal and the agent can store in their memory. Due to different information states, the agent's actual effort a_t might deviate from the incited effort $\tilde{a}_t$. However, the principal has no information about the actual effort a_t and, therefore, bases her estimation of the exogenous factor in t on the incited effort. She computes her estimation according to

$$\tilde{\theta}_t = x_t - \tilde{a}_t \ . \tag{8}$$

The agent, in contrast, knows the actual effort a_t he made and, therefore, can compute the actual exogenous factor in t according to

$$\theta_t = x_t - a_t \ . \tag{9}$$

The principal and the agent store their estimations and observations in their memories. Once their capacities, m_P for the principal and m_A for the agent, are reached, the oldest information is replaced by the latest estimation or observation.

Once the simulation moves on to the next timestep, the principal and the agent update the *learned* expected value for the exogenous factor by averaging all privately stored estimations/observations. To do so, they retrieve the information from their memories. Let us denote the estimations of the exogenous factor available to the principal in t by

$$\boldsymbol{\Theta}_{Pt} = \begin{cases} [\tilde{\theta}_1, \ldots, \tilde{\theta}_{t-1}] & \text{if } m_P = \infty \ , \\ [\tilde{\theta}_{t-m_P}, \ldots, \tilde{\theta}_{t-1}] & \text{if } m_P < \infty \text{ and } t \geq m_P \ , \\ [\tilde{\theta}_1, \ldots, \tilde{\theta}_{t-1}] & \text{if } m_P < \infty \text{ and } t < m_P \ . \end{cases} \tag{10}$$

For the agent, we denote the observations of the exogenous factor available in t by

$$\boldsymbol{\Theta}_{At} = \begin{cases} [\theta_1, \ldots, \theta_{t-1}] & \text{if } m_A = \infty \\ [\theta_{t-m_A}, \ldots, \theta_{t-1}] & \text{if } m_A < \infty \text{ and } t \geq m_A \\ [\theta_1, \ldots, \theta_{t-1}] & \text{if } m_A < \infty \text{ and } t < m_A \end{cases} \tag{11}$$

The principal and the agent compute their *learned* expected value of the exogenous factor in t as the mean $\varnothing(\cdot)$ of the information available to them: For the principal, the *learned* expected value of the exogenous factor is $\hat{\theta}_{Pt} = \varnothing(\boldsymbol{\Theta}_{Pt})$, while for the agent it is computed according to $\hat{\theta}_{At} = \varnothing(\boldsymbol{\Theta}_{At})$. Note that the *learned* expected exogenous factor can also be interpreted as the principal's and the agent's information about (and perception of) the environment since it represents how they regard the environment in that timestep.

3.2.3 The principal's and agent's decisions

The principal's and the agent's decisions revolve around the selection of actions and the computation of the corresponding premium parameters. We denote the set of feasible actions from the perspective of the principal and the agent by $\mathbf{A}_{Pt}$ and $\mathbf{A}_{At}$, respectively. The participation constraint defines the lower boundary of these spaces, and the upper limit is given by the incentive compatibility constraint (Holmström 1979; Leitner and Wall 2021). Recall that the computation of the two constraints includes the expectation about the exogenous factor (see Eqs. 3b and 3c). Thus, if the principal and the agent have the same (different) expectations about the environment, $\mathbf{A}_{Pt}$ and $\mathbf{A}_{At}$ perfectly coincide (are different).

3.2.3.1 The principal's decision

In every timestep, the principal can adapt the premium parameter in the contract. To do so, she randomly discovers two alternative effort levels in the action space $\mathbf{A}_{Pt}$, $\hat{a}_1$ and $\hat{a}_2$, which together with the incited effort of the previous period $\tilde{a}_{t-1}$ serve as candidates for the effort she wants the agent to make in period t. Let us denote the set of candidates for the incited effort in t by $\tilde{\mathbf{A}}_{Pt} = [\hat{a}_1, \hat{a}_2, \tilde{a}_{t-1}]$. Then, the principal undertakes a step-by-step local search, adhering to a hill climbing strategy. This implies that, based on the information available to her at any given moment, she opts for the most promising choice (Cormen et al. 2022). In line with the production function in Eq. 5, the principal computes the expected outcome for all alternatives $a' \in \tilde{\mathbf{A}}_{Pt}$ according to

$$\tilde{x}_{Pt}(a') = a' + \hat{\theta}_{Pt} \ . \tag{12}$$

The principal also computes the premium parameters for all candidate effort levels $a' \in \tilde{\mathbf{A}}_{Pt}$ according to

$$\rho_t(a') = \underset{\rho \in [0,1]}{\arg\max}\, U_P(\tilde{x}_{Pt}(a'), s(\tilde{x}_{Pt}(a'))) \ , \tag{13}$$

and finally selects the candidate which maximizes her utility as the incited effort for the period t according to

$$\tilde{a}_t = \underset{a' \in \tilde{\mathbf{A}}_{Pt}}{\arg\max}\, U_P(\tilde{x}_{Pt}(a'), s(\tilde{x}_{Pt}(a'))) \tag{14}$$

Together with the task that is to be carried out (which is the same throughout all time steps), the corresponding premium parameter $\rho_t := \rho_t(\tilde{a}_t)$ is the main element of the contract that is offered to the agent.

3.2.3.2 The agent's decision

In every timestep, the agent makes two decisions. First, he decides whether to accept or reject the contract offered by the principal. In particular, if the utility of the offered contract exceeds the reservation utility the agent accepts the contract. To make this decision, the agent computes the effort that maximizes his utility given the offered contract according to

$$a_t^* = \underset{a' \in \mathbf{A}_{At}}{\arg\max}\, U_A(s(\tilde{x}_{At}(a')), a') \ , \tag{15}$$

where $\tilde{x}_{At}(a') = a' + \tilde{\theta}_{At}$. If the utility of this effort level exceeds or is equal to the agent's reservation utility, $U_A(s(x_t), a_t^*) \geq \overline{U}$, the agent accepts the contract and makes this effort in t. In consequence, $a_t := a_t^*$.[3]

3.3 Parameter settings and observations

3.3.1 Parameter settings

3.3.1.1 Parameters for scenarios with unlimited information access

The solution proposed in Holmström (1979) aids as the benchmark solution in our study. To show that the proposed model is capable of replicating the benchmark solution, we first run simulations on scenarios with unlimited information access for the principal and the agent, i.e., we set the variables m_A and m_P equal to ∞. In addition, we take into account the turbulence of the environment: Recall the exogenous variable follows a Normal Distribution, which allows us to control the turbulence via the standard deviation. In particular, we set the mean of the Normal Distribution to zero and define its standard deviation relative to the optimal outcome x^* of Holmström's hidden action model (see and Appendix A), so that $\sigma = \{0.05x^*, 0.25x^*, 0.45x^*\}$).

All other parameters are kept constant during the simulation runs. For scenarios with unlimited information access, our analysis focuses memory on the first $T = 200$ timesteps in every simulation round. Every scenario is repeated $R = 700$ times.[4] We set the Arrow-Pratt measure of risk aversion at 0.5 to represent agents with moderate risk aversion, aligning with the findings of Graham, Harvey, and Puri (2013) and Brenner (2015). These studies indicate that CEOs exhibit lower risk aversion compared to the broader population and that the behavior of executives is consistent with a moderate level of risk aversion.

3.3.1.2 Parameters for scenarios with limited information access

To capture the effects of limited information access in hidden action setups, we analyze scenarios with three different values for the principal's memory ($m_P =$

3. Please note that, without loss of generality, we normalize the reservation utility to zero during the simulation experiments, and make sure that the agent accepts the contract in all cases.

4. We follow the approach proposed in Lee et al. (2015) and select the number of simulation rounds based on the coefficient of variation. For our settings, this measure stabilizes at $\epsilon \leq 0.01$ at around 700 repetitions.

$\{1, 3, 5\}$) and the agent's memory ($m_A = \{1, 3, 5\}$), whereby this parameter can be interpreted so that the poorer the memory, the lower the information availability.[5]

The analysis of scenarios with limited memory focuses on the first $T = 20$ timesteps in every simulation round; we do so because most of the dynamics can be observed within this period. All other parameters are kept constant during the simulation runs. An overview of the parameters considered in this simulation study is provided in Tab. 3.

Parameter	Notation	Limited memory	Unlimited memory
Subject to variation:			
Principal's memory	m_P	$1, 3, 5$	∞
Agent's memory	m_A	$1, 3, 5$	∞
Exogenous factor: standard deviation	σ	$0.05x^*$, $0.25x^*$, $0.45x^*$	$0.05x^*$, $0.25x^*$, $0.45x^*$
Constants:			
Exogenous factor: mean	μ	0	0
Agent's Arrow-Pratt measure	η	0.5	0.5
Observation period	T	20	200
Simulation rounds	R	700	700

Tab. 3: Simulation parameters for scenarios with unlimited and limited memory

3.3.2 Observations

In our simulation experiments, we observe four measures: (i) the premium parameter determined by the principal, (ii) the level of effort exerted by the agent in

5. We limit the parameter space because of the computational complexity of the simulation model. The computation time T^{comp} for a simulation model with p parameters and l levels per parameter is l^p, scaling polynomially with the number of levels l per parameter. For example, with $p = 3$ and $l = 3$, the parameter space is $3^3 = 27$, and the initial computation time is $T_0^{\text{comp}} = 27 \cdot T^{\text{sim}}$, with $T^{\text{sim}} \approx 640$ minutes for $T = 20$ time steps per simulation run. Adding n levels per parameter changes the parameter space to $(l+n)^p$ and the computation time to $T_n^{\text{comp}} = (l+n)^p \cdot T^{\text{sim}}$, resulting in a computation time ratio of $T_n^{\text{comp}}/T_0^{\text{comp}} = ((l+n)/l)^p$. Thus, for $n = 1$ the computation time approximately doubles (≈ 2.37), with $n = 2$ it quadruples (≈ 4.63), and with $n = 3$ it octuples.

completing the given task, (iii) the utility experienced by the agent throughout the experiments, and (iv) the utility of the principal.

As introduced in Eq. 6, the *premium parameter* defines the agent's share of the task outcome. We denote the premium parameter that is effective in period t and simulation run r by ρ_{tr} and the premium parameter effective in the optimal solution by ρ^* (see Appendix A). We compute the average normalized premium parameter in every timestep according to

$$\tilde{\rho}_t = \frac{1}{R} \sum_{r=1}^{R} \frac{\rho_{tr}}{\rho^*} \ . \tag{16}$$

To capture the effort the agent makes to carry out his task, we report the average normalized actual effort level in every timestep t. We compute this metric as follows:

$$\tilde{a}_t = \frac{1}{R} \sum_{r=1}^{r=R} \frac{a_{tr}}{a^*} \ , \tag{17}$$

where a_{tr} indicates the effort made by the agent in timestep t and simulation run r, and a^* stands for the optimal level of effort suggested in Holmström (1979) (see Appendix A). Please note that the average normalized effort is also a proxy of the task outcome at the macro level, as the outcome is a function of the agent's effort and the exogenous variable (see Eq. 5).

Lastly, we document the utility experienced by both the principal and the agent throughout the simulation runs. For the principal, we denote the utility experienced in time step t and simulation run r by U_{Prt} (see Eq. 4) and normalize it by the utility that can be achieved with the solution of Holmström's hidden action model, which we denote by U_P^* (for its computation see Appendix A). Then, the principal's average normalized utility at time t is computed according to

$$\tilde{U}_{Pt} = \frac{1}{R} \sum_{r=1}^{R} \frac{U_{Prt}}{U_P^*} \ . \tag{18}$$

Similarly, we denote the agent's utility (see Eq. 7) in timestep t and simulation run r and the utility following Holmström's model by U_{Art} and U_A^*, respectively. We compute the agent's average normalized utility at time t by

$$\tilde{U}_{At} = \frac{1}{R} \sum_{r=1}^{R} \frac{U_{Art}}{U_A^*} \ . \tag{19}$$

4 Results

The results are organized into four sections. In Sec. 4.1, we show that the solution emerging from the agent-based model converges to the optimal solution suggested by Holmström (1979). Then, Sec. 4.2 analyzes the scenarios with limited information access. Specifically, Sec. 4.2.1 analyzes the effects of limited information on the premium parameter, Sec. 4.2.2 provides an analysis of the effort made by the agent, and Sec. 4.2.3 focuses on the dynamics within the agent-based model and particularly emphasizes the principal's and the agent's respective utilities that result from the choices related to the premium parameter and the effort.

4.1 Scenarios with unlimited information access: Replicating the benchmark solution

Our first simulations aim at demonstrating that the observations from our agent-based model align with the optimal solution proposed by Holmström (1979) (given the utility functions specified in Sec. 3.2.1). In these simulations, both the principal and the agent are endowed with unlimited memory concerning the environmental variable. It can be expected that with a sufficiently long observation period, the principal's and the agent's estimations of the environmental variable will converge to a value close to its expected value, and following this, we expect the emergence of solutions that are close to the ones proposed in Holmström (1979) from the agent-based model.

To observe the model's actual behavior, we run simulations for an observation period of 200 timesteps and track all observations as detailed in Sec. 3.3.2. For a summary of all parameters, see Tab. 3. To account for the requirement of long (practically infinite) observation periods, we have fitted power models of the form $x(t) = a \cdot t^b + c$ to extrapolate the observed time series over longer periods. The parameters for these models are listed in Tab. 4. Generally, we can see from the results that the exponent b is negative for all models. When t increases, the term t^b converges to zero because of negative values of b; in consequence, the term $a \cdot t^b$ also approaches zero, and the result of the function $x(t)$ will converge to the value of the constant c. The values of c (considering the confidence intervals with $\alpha = 0.05$) are sufficiently close to 1. Therefore (and as we normalize our observations), we conclude that, for a sufficiently extended observation period, our model predictions align closely with the theoretical solutions proposed by Holmström (1979), given the utility functions specified in Sec. 3.2.1.

To assess the convergence rate of $x(t)$ toward the constant c, we define the coefficient-exponent influence ratio (CEIR), $R = |a/b|$. This ratio is calculated for each pair (a, b) and presented in Tab. 4. The CEIR facilitates a comparative analysis; a lower CEIR indicates faster convergence of $x(t)$ to c, whereas a higher CEIR suggests slower convergence.[6] The results reveal that environmental turbulence has a negligible impact on the convergence rates of both the agent's effort and the principal's utility. In contrast, the convergence of the premium parameter and the agent's utility to c is notably slower in turbulent conditions. Moreover, the analysis of the CEIRs indicates that the agent's effort and the principal's utility consistently converge more rapidly to c than the premium parameter and the agent's utility.

4.2 Scenarios with limited information access

For every scenario, we monitor R time series of the measurements described in Sec. 3.3.2, each with a duration of T periods. This includes observing 700 time series of length 20 for scenarios with limited memory, covering all four metrics.

To verify if a series length of 20 is adequate, we define two time windows within the series and compare their central tendencies with a Mann-Whitney U Test (Mann and Whitney 1947), and their variances with a Levene Test (Levene 1960). Our focus is on the series' last quarter, identifying segments from periods 15 to 17 and 18 to 20, utilizing samples from $700{*}3 = 2,100$ observations. We consider a time series length of 20 adequate if we can accept the null hypotheses of the Mann-Whitney U Test (indicating equal central tendencies) and the Levene Test (suggesting equal variances) at significance levels of either $p \leq 0.01$ or $p \leq 0.05$. The corresponding results are included in Tabs. 5 through 8.

To evaluate if altering the principal's or the agent's memory impacts the observed time series, we conduct a Mann-Whitney U Test comparing two related time series (Lee et al. 2015). If we cannot accept the null hypothesis of equal central tendencies at $p \geq 0.05$ or $p \geq 0.01$, we infer that the memory capacity influences the central tendency. Furthermore, to determine the magnitude of this

6. The convergence rate of $x(t)$ towards c is dictated by its derivative's magnitude, expressed as $|x'(t)| = |a| \cdot |b| \cdot t^{b-1}$. Please note that the term $a \cdot t^b$ in the power function $x(t) = a \cdot t^b + c$ is dominated by b, due to the power law dynamics; b determines the rate of change and a only scales this effect. Consequently, a higher $|b|$ results in a more responsive model to variations in t. High CEIRs, where $|a|$ exceeds $|b|$, suggest that the scaling effect of a predominates, leading to a relatively slower convergence of $x(t)$ towards c. Conversely, low CEIRs imply that b's influence is greater relative to a, facilitating a quicker convergence of $x(t)$ to c.

	Estimated power model parameters						CEIR	Goodness	
Observation	a	CI	b	CI	c	CI	|a/b|	R^2	RMSE
Relatively stable environment:									
Premium parameter	-0.8291	±0.0105	-0.4516	±0.0133	1.0471	±0.0064	1.8359	0.9927	0.0077
Effort level	-0.5308	±0.0111	-0.9558	±0.0267	1.0030	±0.0040	0.5553	0.9830	0.0061
Principal's utility	-0.5176	±0.0117	-1.0140	±0.0308	1.0011	±0.0013	0.5105	0.9799	0.0063
Agent's utility	-0.9053	±0.0149	-0.4919	±0.0467	1.0394	±0.0072	1.8404	0.9886	0.0104
Mid-turbulent environment:									
Premium parameter	-0.7497	±0.0080	-0.3601	±0.0120	1.0111	±0.0082	2.0819	0.9942	0.0063
Effort level	-0.4974	±0.0068	-0.8460	±0.0157	0.9890	±0.0010	0.5879	0.9929	0.0038
Principal's utility	-0.4842	±0.0172	-0.9012	±0.0431	0.9918	±0.0023	0.5373	0.9529	0.0096
Agent's utility	-0.8002	±0.0139	-0.3881	±0.0191	0.9823	±0.0120	2.0618	0.9853	0.0108
Turbulent environment:									
Premium parameter	-0.7143	±0.0130	-0.2841	±0.0172	1.0264	±0.0176	2.5143	0.9886	0.0083
Effort level	-0.4491	±0.0079	-0.7800	±0.0389	0.9822	±0.0013	0.5758	0.9882	0.0045
Principal's utility	-0.4449	±0.0309	-0.8398	±0.0791	0.9860	±0.0047	0.5298	0.8434	0.0175
Agent's utility	-0.7342	±0.0239	-0.3135	±0.0345	0.9389	±0.0302	2.3419	0.9537	0.0174

Estimated power models have the form of $x(t) = a \cdot t^b + c$.
CI columns report the confidence intervals for $\alpha = 0.05$.
CEIR column reports the coefficient-exponent influence ratio, $|a/b|$.
Goodness columns report the Coefficient of Determination (R^2) and the Root Mean Squared Error (RMSE) as two measures for the models' fit.

Tab. 4: Estimated parameters for fitted power models for scenarios with unlimited information access impact, we calculate the rank biserial correlation as an effect size indicator. This is done using the approach outlined in Wendt (1972) who computes the rank biserial correlation as follows: $r_{rb} = 1 - (2 \cdot U)/(n_1 \cdot n_2)$, where U is the Mann-Whitney U Test statistic, and n_1 and n_2 are the sizes of the two compared samples. The results are detailed in Tabs. 9 and 10.

4.2.1 Premium parameter

This section examines the impact of information constraints on the premium parameter. We document our findings by first presenting the mean of the average normalized premium parameters throughout the entire observation period and, at the end of this period, alongside their respective confidence intervals in Tab. 5. Further, the analysis of the time series behavior is also included in Tab. 5. All time series for the premium parameter demonstrate stability in both their central tendencies and variances.

The results indicate that, in general, the premium parameter decreases with higher environmental turbulence. Please note that the turbulence *perceived* by the principal and the agent is also affected by their memories. Recall the principal's and the agent's memories introduced in Eqs. 10 and 11, respectively: The higher the memory, the more estimations/observations of the exogenous variable are taken into account when the learned expectation about the exogenous variable is computed. Thus, more memory translates into more precise expectations and, as a consequence, less perceived turbulence over time. The premium parameter is the highest (lowest) in stable (turbulent) environments in all subplots.

A closer look at the effects of the principal's and the agent's respective information in this context reveals that better informed principals will set higher premium parameters. In contrast, for increases in the agent's memory, no significant effects on the premium parameter can be observed. This insight is in line with expectation since the principal designs the contract (thereby fixing the premium parameter).

4.2.2 Agent's effort

This section focuses on analyzing how the agent's behavior responds to the the principal's premium parameter. We present data on the agent's normalized effort, averaged across the entire observation period, and at the observation period's conclusion, along with the corresponding confidence intervals and an analysis of the time series behavior, in Tab. 6. Please note that every effort time series shows

Memory		Expected premium parameter				Stationarity	
Principal	Agent	Periods 1:20	CI	Period 20	CI	Central tendency	Variance
Relatively stable environment:							
1	1	0.6090	±0.0045	0.6585	±0.0167	**	**
1	3	0.6136	±0.0045	0.6596	±0.0169	**	**
1	5	0.6045	±0.0045	0.6571	±0.0164	**	**
3	1	0.6660	±0.0047	0.7422	±0.0152	**	**
3	3	0.6533	±0.0046	0.7353	±0.0150	**	**
3	5	0.6539	±0.0046	0.7294	±0.0163	**	**
5	1	0.6771	±0.0047	0.7653	±0.0157	**	*
5	3	0.6805	±0.0047	0.7739	±0.0150	**	**
5	5	0.6737	±0.0047	0.7635	±0.0151	**	**
Mid-turbulent environment:							
1	1	0.5089	±0.0045	0.5215	±0.0193	**	**
1	3	0.5164	±0.0046	0.5346	±0.0193	**	**
1	5	0.5159	±0.0045	0.5456	±0.0184	**	**
3	1	0.5726	±0.0046	0.6106	±0.0178	**	**
3	3	0.5702	±0.0045	0.6081	±0.0186	**	**
3	5	0.5706	±0.0046	0.6020	±0.0189	**	*
5	1	0.6045	±0.0045	0.6447	±0.0174	**	**
5	3	0.5985	±0.0046	0.6609	±0.0170	**	*
5	5	0.6008	±0.0045	0.6524	±0.0179	*	**
Turbulent environment:							
1	1	0.4897	±0.0050	0.5053	±0.0219	**	**
1	3	0.5008	±0.0051	0.5143	±0.0215	**	**
1	5	0.5065	±0.0052	0.5367	±0.0228	**	**
3	1	0.5417	±0.0046	0.5739	±0.0185	**	**
3	3	0.5426	±0.0046	0.5608	±0.0201	**	**
3	5	0.5467	±0.0047	0.5787	±0.0191	**	**
5	1	0.5655	±0.0046	0.6043	±0.0189	**	**
5	3	0.5680	±0.0046	0.6054	±0.0181	**	**
5	5	0.5721	±0.0046	0.6120	±0.0185	**	**

CI columns report the confidence intervals for $\alpha = 0.01$.
Stationarity columns report results of a Mann-Whitney U Test (central tendency) and a Levene Test (variance).
$*$ null hypothesis can be accepted with $p \leq 0.01$.
$**$ null hypothesis can be accepted with $p \leq 0.05$.

Tab. 5: Expected premium parameters and stationarity of time series stable central tendencies, and with the exception of one series, this stability extends to their variances as well.

The results indicate that the agent responds to the incentives provided by the principal, since higher premium parameters result in more effort. Section 4.2.1 discussed that the premium parameter increases as the environmental turbulence decreases, which also holds true for the agent's effort. It is remarkable that—for scenarios with relatively well informed principals and relatively stable environments—the effort reaches a level of around 95% of of the optimal effort suggested in Holmström (1979).

In environments characterized by mid-level turbulence and high turbulence, agent's effort is notably lower than in more stable contexts. Yet, our findings suggest that the degree of turbulence (as soon as mid-level turbulence occurs) has a minimal impact, as the variation in agent effort between mid-turbulent and highly turbulent environments is slight. We also observe that the influence of the principal's information on agent's effort becomes more pronounced in relatively stable environments.

4.2.3 Principal's and agent's utilities

This section focuses on analyzing the effects of limited information on the principal's and agent's utilities. We compute the average normalized utility across the entire observation period, its value at the period's end, and the corresponding confidence intervals. Additionally, we include an analysis of the time series behavior. The findings related to the utilities of both the agent and the principal are presented in Tabs. 7 and 8, respectively. Our analysis indicates that all utility time series maintain stability in terms of central tendencies and variances.

The results suggest that limitations in information significantly decrease the agent's utility in all cases.[7] In the worst case, the agent loses around 60% of his utility, while the lost utility amounts to only about 24% in the best case. The agent's utility follows the pattern of the premium parameter presented in Tab. 5. First, increases in (perceived) environmental turbulence decrease the agent's utility. Second, if the principal is better informed about the environment, the agent's utility increases. Third, no significant effects on utility can be observed if the extent of information available to the agent increases. These are exciting findings

7. Please note that by the construction of the performance measures in Eqs. 18 and 19, the utilities achievable with the solution proposed in Holmström (1979) take a value of 1.

Memory		Expected effort				Stationarity	
Principal	Agent	Periods 1:20	CI	Period 20	CI	Central tendency	Variance
Relatively stable environment:							
1	1	0.8639	±0.0037	0.9074	±0.0107	**	n.s.
1	3	0.8664	±0.0037	0.9062	±0.0108	**	**
1	5	0.8595	±0.0038	0.9066	±0.0106	**	**
3	1	0.8889	±0.0036	0.9424	±0.0091	**	**
3	3	0.8833	±0.0037	0.9426	±0.0082	**	**
3	5	0.8845	±0.0036	0.9359	±0.0096	**	**
5	1	0.8934	±0.0037	0.9489	±0.0086	**	*
5	3	0.8958	±0.0036	0.9516	±0.0084	**	**
5	5	0.8923	±0.0036	0.9503	±0.0081	**	**
Mid-turbulent environment:							
1	1	0.8025	±0.0045	0.8209	±0.0179	**	**
1	3	0.8045	±0.0042	0.8266	±0.0158	**	**
1	5	0.8037	±0.0040	0.8368	±0.0148	**	**
3	1	0.8453	±0.0042	0.8820	±0.0150	**	**
3	3	0.8431	±0.0040	0.8799	±0.0141	**	**
3	5	0.8413	±0.0039	0.8713	±0.0143	**	**
5	1	0.8665	±0.0041	0.9033	±0.0147	**	**
5	3	0.8582	±0.0040	0.9085	±0.0116	*	*
5	5	0.8622	±0.0037	0.9047	±0.0122	**	**
Turbulent environment:							
1	1	0.7985	±0.0057	0.8179	±0.0246	**	**
1	3	0.7896	±0.0049	0.8093	±0.0190	**	**
1	5	0.7887	±0.0046	0.8188	±0.0181	**	**
3	1	0.8309	±0.0050	0.8596	±0.0191	**	**
3	3	0.8290	±0.0045	0.8472	±0.0185	**	**
3	5	0.8294	±0.0044	0.8648	±0.0160	**	**
5	1	0.8470	±0.0051	0.8882	±0.0202	**	**
5	3	0.8438	±0.0044	0.8795	±0.0154	**	**
5	5	0.8480	±0.0042	0.8860	±0.0153	**	**

CI columns report the confidence intervals for $\alpha = 0.01$.
Stationarity columns report results of a Mann-Whitney U Test (central tendency) and a Levene Test (variance).
$*$ null hypothesis can be accepted with $p \leq 0.01$.
$**$ null hypothesis can be accepted with $p \leq 0.05$.
n.s. not significant.

Tab. 6: Agent's expected effort and stationarity of time series since the agent's utility is composed of two components (see Eq. 7): First, the utility of compensation which is mainly in the sphere of control of the principal who can control the utility via the premium parameter. Second, the disutility of making an effort, which, on the contrary, is in the agent's sphere of control since he autonomously decides about the action. The results in Tab. 8 indicate that the principal attains a near-optimal utility in all scenarios. What is particularly surprising is that—irrespective of the environmental turbulence, the principal's and the agent's memories—the principal's utility is at almost the same level in all scenarios.

The findings outlined above suggest that the principal's utility remains relatively unaffected by constraints on her own or the agent's information. To explore this further, we statistically assess whether modifications in memory capacities lead to meaningful differences in the normalized average utilities. The significance of these variations, along with the rank biserial correlation for measuring the effect size, is documented in Tabs. 9 and 10.

Tab. 10 indicates that variations in the agent's memory in most cases does not significantly affect outcomes, and when they do, the magnitude of these effects is quite small, implying a limited role of the agent's memory in determining outcomes. On the other hand, changes in the principal's memory significantly affect both the principal's and the agent's utilities, as shown in Tab. 9. Notably, the agent's utility demonstrates a higher sensitivity to changes in the principal's memory, with effect sizes for the principal's utility becoming minimal in environments of medium to high turbulence. This suggests that there is reduced motivation for the principal, who aims to maximize utility, to increase her memory capacity. Additionally, the advantage of enhanced memory on utilities decreases as environmental complexity rises, highlighting that the most substantial positive effects are seen in more stable conditions.

5 Discussion

The results presented in Sec. 4 allow to put the effects of limitations in the principal's and agent's respective information and environmental turbulence in the following framework (see Fig. 3): Recall, the principal and the agent estimate and observe the exogenous variable in every timestep, respectively. Then, they store their estimations/observations in their memories. Limitations in their respective information take effect in the form of constraints in their memories. The more informed the principal and the agent are, the more information stored in their memories are considered when computing the *learned* expectation of the exogenous

Memory		Agent's expected utility				Stationarity	
Principal	Agent	Periods 1:20	CI	Period 20	CI	Central tendency	Variance
Relatively stable environment:							
1	1	0.5838	±0.0052	0.6403	±0.0195	**	**
1	3	0.5884	±0.0052	0.6426	±0.0201	**	**
1	5	0.5786	±0.0053	0.6379	±0.0195	**	**
3	1	0.6477	±0.0054	0.7357	±0.0177	**	**
3	3	0.6344	±0.0054	0.7299	±0.0176	**	**
3	5	0.6344	±0.0053	0.7207	±0.0190	*	**
5	1	0.6597	±0.0054	0.7610	±0.0181	**	*
5	3	0.6639	±0.0054	0.7716	±0.0172	**	**
5	5	0.6571	±0.0054	0.7594	±0.0175	**	**
Mid-turbulent environment:							
1	1	0.4494	±0.0065	0.4657	±0.0294	*	**
1	3	0.4602	±0.0065	0.4778	±0.0281	**	**
1	5	0.4611	±0.0065	0.4807	±0.0275	**	**
3	1	0.5222	±0.0066	0.5664	±0.0272	**	**
3	3	0.5229	±0.0065	0.5679	±0.0276	**	**
3	5	0.5260	±0.0066	0.5545	±0.0273	**	**
5	1	0.5585	±0.0065	0.6100	±0.0285	**	**
5	3	0.5578	±0.0067	0.6271	±0.0283	**	*
5	5	0.5597	±0.0065	0.6207	±0.0280	*	**
Turbulent environment:							
1	1	0.3880	±0.0085	0.3967	±0.0388	**	**
1	3	0.4150	±0.0087	0.4194	±0.0380	**	*
1	5	0.4210	±0.0089	0.4856	±0.0408	**	**
3	1	0.4524	±0.0089	0.4838	±0.0395	**	**
3	3	0.4597	±0.0090	0.4707	±0.0383	**	**
3	5	0.4617	±0.0090	0.4932	±0.0403	**	**
5	1	0.4757	±0.0091	0.5133	±0.0411	**	**
5	3	0.4930	±0.0089	0.5272	±0.0397	**	**
5	5	0.4933	±0.0091	0.5457	±0.0406	**	**

CI columns report the confidence intervals for $\alpha = 0.01$.
Stationarity columns report results of a Mann-Whitney U Test (central tendency) and a Levene Test (variance).
$*$ null hypothesis can be accepted with $p \leq 0.01$.
$**$ null hypothesis can be accepted with $p \leq 0.05$.

Tab. 7: Agent's expected utility and stationarity of time series

Memory		Principal's expected utility				Stationarity	
Principal	Agent	Periods 1:20	CI	Period 20	CI	Central tendency	Variance
Relatively stable environment:							
1	1	0.8780	±0.0038	0.9208	±0.0111	**	**
1	3	0.8798	±0.0038	0.9200	±0.0118	**	**
1	5	0.8738	±0.0039	0.9179	±0.0115	**	**
3	1	0.9007	±0.0038	0.9526	±0.0102	**	**
3	3	0.8959	±0.0038	0.9552	±0.0095	**	**
3	5	0.8965	±0.0038	0.9460	±0.0109	**	**
5	1	0.9042	±0.0038	0.9594	±0.0097	**	**
5	3	0.9066	±0.0037	0.9626	±0.0091	**	**
5	5	0.9041	±0.0037	0.9604	±0.0093	*	**
Mid-turbulent environment:							
1	1	0.8163	±0.0072	0.8370	±0.0322	**	**
1	3	0.8186	±0.0069	0.8375	±0.0287	**	**
1	5	0.8198	±0.0068	0.8336	±0.0287	**	**
3	1	0.8576	±0.0071	0.8973	±0.0286	**	*
3	3	0.8576	±0.0068	0.8988	±0.0287	**	**
3	5	0.8575	±0.0068	0.8792	±0.0279	**	**
5	1	0.8785	±0.0069	0.9211	±0.0290	**	**
5	3	0.8745	±0.0069	0.9233	±0.0281	*	**
5	5	0.8773	±0.0066	0.9233	±0.0274	**	**
Turbulent environment:							
1	1	0.8066	±0.0116	0.8222	±0.0524	**	**
1	3	0.8068	±0.0111	0.8148	±0.0470	**	**
1	5	0.8065	±0.0110	0.8830	±0.0479	**	**
3	1	0.8483	±0.0112	0.8790	±0.0482	**	**
3	3	0.8437	±0.0109	0.8461	±0.0472	**	**
3	5	0.8400	±0.0109	0.8718	±0.0476	**	**
5	1	0.8626	±0.0112	0.8931	±0.0475	**	**
5	3	0.8633	±0.0108	0.8876	±0.0455	**	**
5	5	0.8593	±0.0109	0.9042	±0.0470	**	**

CI columns report the confidence intervals for $\alpha = 0.01$.
Stationarity columns report results of a Mann-Whitney U Test (central tendency) and a Levene Test (variance).
$*$ null hypothesis can be accepted with $p \leq 0.01$.
$**$ null hypothesis can be accepted with $p \leq 0.05$.

Tab. 8: Principal's expected utility and stationarity of time series

Memory			Increases in principal's memory			
			1→3	1→5	1→3	1→5
Principal	Agent	Metric	Principal's utility		Agent's utility	
Relatively stable environment:						
1	1	Significance	**	**	**	**
		Effect size	0.1193	0.1354	0.1837	0.2156
1	5	Significance	**	**	**	**
		Effect size	0.1059	0.1492	0.1526	0.2171
Mid-turbulent environment:						
1	1	Significance	**	**	**	**
		Effect size	0.0740	0.1117	0.1425	0.2134
1	5	Significance	**	**	**	**
		Effect size	0.0737	0.1082	0.1297	0.1949
Turbulent environment:						
1	1	Significance	**	**	**	**
		Effect size	0.0470	0.0623	0.0981	0.1332
1	5	Significance	**	**	**	**
		Effect size	0.0362	0.0588	0.0651	0.1102

Significance lines report results of a Mann-Whitney U Test.
Effect size lines report the rank biserial correlations.
$**$ null hypothesis cannot be accepted with $p \geq 0.05$.

Tab. 9: Effects of increases in the principal's memory on the principal's and the agent's utilities

Memory			Increases in agent's memory			
			1→3	1→5	1→3	1→5
Principal	Agent	Metric	Principal's utility		Agent's utility	
Relatively stable environment:						
1	1	Significance	n.s.	n.s.	$*$	n.s.
		Effect size	0.0085	-0.0112	0.0157	-0.0089
5	1	Significance	n.s.	n.s.	n.s.	n.s.
		Effect size	0.0090	0.0026	0.0097	-0.0107
Mid-turbulent environment:						
1	1	Significance	n.s.	n.s.	$*$	$*$
		Effect size	0.0045	0.0058	0.0215	0.0221
5	1	Significance	n.s.	n.s.	n.s.	n.s.
		Effect size	-0.0039	-0.0029	-0.0001	0.0010
Turbulent environment:						
1	1	Significance	n.s.	n.s.	$**$	$**$
		Effect size	0.0030	0.0044	0.0351	0.0437
5	1	Significance	n.s.	n.s.	$*$	$*$
		Effect size	0.0020	-0.0017	0.0209	0.0225

Significance lines report results of a Mann-Whitney U Test.
Effect size lines report the rank biserial correlations.
$*$ null hypothesis cannot be accepted with $p \geq 0.01$.
$**$ null hypothesis cannot be accepted with $p \geq 0.05$.
n.s.: central tendencies of observations are not significantly different.

Tab. 10: Effects of increases in the agent's memory on the principal's and the agent's utilities variable. Thus, their respective information moderates the principal's and agent's *perceptions* of the environment. The principal's perception affects her choice of the premium parameter. One might expect that the agent's perception of the environment impacts his effort choice, but we could not observe significant influences for this relationship. Together with the actual environment, the principal's and the agent's decisions about the premium parameter and the effort, respectively, affect their utilities. The analysis in this paper focuses mainly on the effects of turbulence in the environment and limitations in the principal's and agent's respective information in this framework (which is indicated by the gray boxes in Fig. 3).

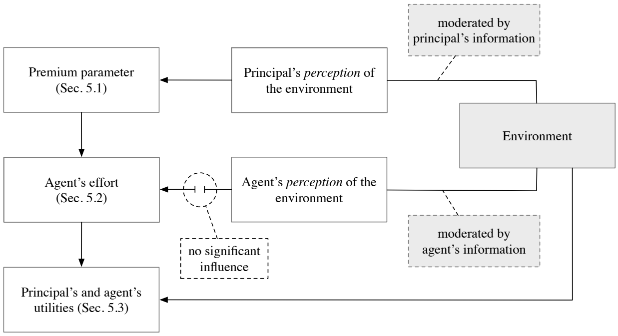

Fig. 3: Framework for limited information in hidden action situations

5.1 Results related to the premium parameter

The main findings presented in Sec. 4.2.1 are that *(i)* the value of the premium parameter decreases with environmental turbulence and *(ii)* increases with the principal's information. This means that the agent's share of the outcome is relatively small (large) if the environment is rather turbulent (stable). However, if the turbulence is high, the agent cannot easily control the outcome, which puts his compensation at risk (Miceli and Heneman 2000). Accordingly, the finding that the (perceived) turbulence decreases the premium parameter is (in part) contrary to the risk premium hypothesis. This hypothesis states that the principal will have to increase the risk-averse agent's total compensation in turbulent environments to protect him from risk (Eisenhardt 1988; Umanath, Ray, and Campbell 1993; Burns and Stalker 2001). Counter-intuitively, the results presented in Sec. 4.2.1 indicate the contrary. Even though the risk-bearing is initially within the principal's role (Fama and Jensen 1983), she shifts a part of the risk to the agent.

This finding not only contradicts the risk premium hypothesis but is also in contrast to previous research on task programmability and the predictions of classical organization theory. Stroh et al. (1996) and Sung and Choi (2012) link environmental turbulence with task programmability by arguing that more (less) turbulence can be interpreted in terms of less (more) programmable tasks since task situations and problems change more frequently in turbulent environments. Furthermore, it is often suggested that task programmability is negatively correlated with the magnitude of variable compensation components (Gomez-Mejia and Balkin 1992). This translates into the expectation that more environmental turbulence (and less task programmability) should be linked to higher proportions of variable compensation and vice versa (Stroh et al. 1996; Gerhart and Milkovich 1990). This expectation is also in line with classical organization theory (Thompson 1967), which predicts that organizations that operate in turbulent environments rely more heavily on variable compensation to ensure the appropriate behaviors of their agents. Our findings do not support this expectation but can be linked to the argumentation provided in Smith (1984). There are not just drawbacks but also advantages of turbulent environments (Eisenhardt 1989), and an analogy of agents who are hired in risky environments and 'unfair lotteries' can be established: The *average* pay is not necessarily high, but there is a chance to receive a high compensation, even though perhaps this chance is relatively slight (see also Miceli and Heneman 2000).

5.2 Results related to the agent's effort

The results presented in Sec. 4.2.2 indicate that the agent's effort follows the patterns observed for the premium parameters. The effort decreases with environmental turbulence so that the agent makes more (less) effort in relatively stable (turbulent) environments. If a more informed principal sets the premium parameter, the agent makes significantly more effort. This relation is a fundamental assumption in economic contexts and is supported by experimental research (Dickinson 1999; Takahashi, Shen, and Ogawa 2016) and field research (Banker, Lee, and Potter 1996; Lazear 2000).

Since the agent's average normalized effort is also a proxy for how well the organization performs, these observations can be related to environmental turbulence and firm performance research. Environmental uncertainty and dynamism (Milliken 1987; Chen, Reilly, and Lynn 2005; Aldrich 2008) increase the difficulty of organizational decision-making and significantly affect organizational performance (Reinwald, Leitner, and Wall 2022). This is in line with the results presented in Yu, Wang, and Brouthers (2016), who find that (perceived) environmental uncertainty affects the identification of competitors so that firms identify more competitors if the environment is certain. This directly translates into a more competitive advantage and, as a consequence, a better (worse) performance in certain (uncertain) environments (Dutta and King 1980; Porter 1997). For the hidden action context, it is also shown in Reinwald, Leitner, and Wall (2020) that increases in (perceived) environmental turbulence lead to a drop in firm performance. This finding is also supported by the contingency management accounting literature, which is, amongst others, concerned with the fit between organizations and their environment (Otley 1999, 2016). If the environment is turbulent and/or the principal is not very well informed about the environment, she cannot design the incentive scheme so that it fits the actual environment (Hoque 2005; Chenhall and Morris 1986; Ezzamel 1990; Ghosh and Olsen 2009). Since the agent responds to the incentives set by the principal, suboptimal incentive parameters directly translate into adverse effects on performance.

5.3 Results related to the principal's and the agent's utilities

Above, it was established that the principal's choice of the premium parameter might indicate that she transfers some of the risks to the agent by reducing the premium parameter as environmental turbulence increases. Now, as we take the results related to the agent's utility presented in Sec. 4.2.3 into account, this conjecture becomes even more evident. One would expect that the agent compensates for the additional risk and the missing risk premium by making less effort, which—in turn—eventually increases his utility. However, the results indicate the opposite: The agent's utility decreases with increases in environmental turbulence. If a more informed principal sets the premium parameter, the agent's utility appears to increase. For the principal, the results presented in Sec. 4.2.3 indicate that the volatility of his utility is relatively high. However, the principal's utility appears to be less sensitive to limitations in her own and the agent's information. As a consequence we can conclude that the risk-neutral principal withholds a risk premium from the *risk-averse* agent, which, in turn, assures the robustness of the principal's utility to environmental turbulence.

The results indicate that the agent is over-dependent on the principal, which results in a dilemma for the agent: First, if the agent were able to increase his memory, doing so would *not* allow him to escape the situation, since his memory has no significant effect on his utility. Second, the principal appears to set the premium parameter to punish the agent for the risky environment. However, this would still be the best option for the agent since otherwise, he would have rejected the contract and followed the outside option. Shirking (i.e., putting in less effort) would not be an option either, since it would decrease the agent's utility (Nilakant and Rao 1994). Third, even if the agent were more informed, he would have no incentive to disclose his private information about the environment. If the principal was informed about the actual exogenous variable (instead of estimating it), she could deduce the agent's effort from the outcome (Caillaud and Hermalin 2000). As soon as the principal realizes that the agent discloses this information, she could switch from performance-based pay to effort-based compensation. As a consequence, the principal could further increase her utility at the cost of the agent. Previous research merely addresses the issue of overly dependent agents. It tends to focus on overdependence on the principal's side: Huang, Raimo, and Humfrey (2016), for example, state that the principal's power to exert control decreases with the dependence of the agent. Willcocks and Choi (1995) also focus on the agent's perspective and argue that in vendor-client relationships, the client might be overly dependent on the vendor (see also Hancox and Hackney 2000). Our results indicate that limited information—of both the principal and the agent—appears to empower the principal to (unintentionally) siphon-off utility from the agent by capitalizing on her control over the compensation (David, Kochhar, and Levitas 1998).

Recall that one fundamental foundation of the principal-agent theory is that both the principal and the agent are driven by self-interest (Huang, Raimo, and Humfrey 2016). Now that we know that the principal experiences (almost) the same utility in all cases, she has no incentive to stop transferring risk to the agent or to gather information about the environment on her own (i.e., to increase her information). The principal, thus—perhaps unintentionally—behaves in a way that might be interpreted as opportunism, i.e., self-interest-seeking with guile (Williamson 1975), whereby limitations in the principal's information appear to reinforce behavioral patterns that appear as guile.

5.4 Methodological contributions

From a methodological point of view, we have introduced an agent-based model of the hidden action problem (Holmström 1979) by employing the research approach put forward by Guerrero and Axtell (2011) and Leitner and Behrens (2015a), and we show that the solution of the agent-based model converges to the solution proposed by the original model. Our approach is different from the classical principal-agent theory at a conceptual level. In particular, agent-based modeling and simulation allow systematically analyzing the robustness of the solutions derived from closed-form models to deviations from the assumptions included in these models (Wall and Leitner 2021; Guerrero and Axtell 2011; Leitner 2024). The principal-agent theory often includes some idealized assumptions. Some researchers are concerned that (over-)simplified behavioral assumptions might come at the cost of the validity and explanatory power of the findings (Eden 1989; Mingers and Rosenhead 2004; Mingers 2011). Usually, it is assumed that individual behavior is driven by optimization and rationality, the modeled individuals' choices are representative for the entire population, and equilibrium solutions can be achieved. Our approach, however, allows for the explicit consideration of emergence, limitations in information, and heterogeneity (Chen 2017; Mealy, Farmer, and Teytelboym 2019; Chang and Harrington Jr 2006). These features of our approach allow to overcome some of the limitations of the formal approaches in analytical research: While solutions derived from analytical models are related to narrow behavioral assumptions, the model presented here allows to take rich environmental contexts and relaxed–and perhaps even more realistic—behavioral assumptions into account (Wall and Leitner 2021; Wall 2024). However, the use of agent-based modeling and simulation in microeconomic contexts is rather scarce. Therefore, the approach presented here can be regarded as a step towards a more open approach in microeconomic research that allows for relaxing (some of) the well-established assumptions.

6 Conclusions

In this paper, we proposed an agent-based model of the hidden action problem. In particular, we transferred the closed-form model introduced in Holmström (1979) into an agent-based model (Guerrero and Axtell 2011; Leitner and Behrens 2015a). Doing so allowed us to relax some of the idealized assumptions in Holmström's model related to the principal's and the agent's respective information. We focus on the memory of information about the environment. Our results indicate that the principal's information is the key to good performance, whereas the agent's information does not significantly affect performance. Surprisingly, the principal appears to behave very selfishly by siphoning off utility from the agent to maintain near-optimal personal utility by exerting her control over the agent's compensation. We model (more realistic) human behavior by employing operational research methods and by considering (and bringing together) findings from the disciplines of cognitive psychology, economics, management, and operational research.

Of course, our research is not without limitations. Several further incentive mechanisms—also nonformal ones—might be employed in the modeled situation. Granting the principal degrees of freedom in her choices related to the control mechanism might be a fruitful avenue for future research. We limit the principal's and the agent's respective information concerning memory only. Further research might focus on extending the limitations in information by also taking into account, for example, calculation errors, limitations in other types of information, and biases in information processing. Additionally, the agent makes decisions based on the learned mean value of the environmental variable. Future research could enhance the agent's utility function by incorporating the variance of the environmental variable, thereby more accurately reflecting the agent's risk aversion. Currently, we model scenarios where there is a one-to-one delegation relationship between a single principal and a single agent. Future studies could broaden this framework to include delegation relationships involving multiple agents. Although the focus of this paper is on a theoretical analysis of how the hidden action model withstands limitations in information access, subsequent research might include laboratory experiments to empirically validate the model.

Data and code availability

Simulation data and code are available via the following link:
https://github.com/sforstephan/JBNST24.

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Appendix A Solution to Holmström's hidden action problem

There are two different approaches that can be used to solve the program formalized in Eqs. 3a-3c. Important for us is the approach of Mirrlees (1976), who suppresses θ and views x as a random variable with distribution $F(x, a)$. In this approach, it is assumed that $\forall\, a \in A\, \exists\, x \in \mathbb{R} : F_a(x, a) < 0$ so that a change in a has nontrivial effect on the distribution of x. For a given distribution of θ, $F(x, a)$ is the distribution induced on $x = x(a, \theta)$ (Holmström 1979).

In the following program, $f(x, a)$ is the density function of F with f_a and f_{aa} well defined for all (x, a) and Eq. (3c) is replaced with a first-order constraint. Furthermore, $s(x)$ is restricted to lie in the interval $[c, d + x]$ to guarantee an existing solution to Eqs. 3a-3c for the class of functions in Eq. 20, where $V_b^{b'}$ is the total variation of s in the interval $[b, b']$ (Kolmogorov and Fomin 1970; Holmström 1979).

$$S_K = \{s(x) \in [c, d + x] | V_b^{b'}(s) \leq K \cdot (b' - b)\}, \tag{20}$$

$$\max_{s(x)\in[c,d+x],a} \int G(x - s(x))f(x, a)dx \tag{21a}$$

$$subject\ to \int [U(s(x) - V(a)]f(x, a)dx \geq \bar{H}, \tag{21b}$$

$$\int U(s(x))f_a(x, a)dx = V'(a). \tag{21c}$$

We denote the multipliers for Eqs. 21b and 21c by λ and μ, respectively. After a pointwise Lagrangian optimisation, the optimal sharing rule yields the following characterization:

$$\frac{G'(x - s(x))}{U'(s(x))} = \lambda + \mu \cdot \frac{f_a(x, a)}{f(x, a)}, \tag{22}$$

for almost every x for which Eq. 22 has a solution $s(x) \in [c, d+x]$. Also, μ is given as solution to the adjoint equation and is determined by Eq. 21c (Holmström 1979).

$$\int G(x - s(x))f_a(x, a)dx + \mu\{\int U(s(x))f_{aa}(x, a)dx - V''(a)\} = 0 \tag{23}$$

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