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Information unraveling and limited depth of reasoning ☆

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ABSTRACT

Information unraveling is an elegant theoretical argument suggesting that private information is voluntarily and fully revealed in many circumstances. However, the experimental literature has documented many cases of incomplete unraveling and has suggested limited depth of reasoning on the part of senders as a behavioral explanation. To test this explanation, we modify the design of existing unraveling games along two dimensions. In contrast to the baseline setting with simultaneous moves, we introduce a variant where decision-making is essentially sequential. Second, we vary the cost of disclosure, resulting in a 2×2 treatment design. Both sequential decision-making and low disclosure costs are suitable for reducing the demands on subjects' level-k reasoning. The data confirm that sequential decision-making and low disclosure costs lead to more disclosure, and there is virtually full disclosure in the treatment that combines both. A calibrated level-k model makes quantitative predictions, including precise treatment level and player-specific revelation rates, and these predictions organize the data well. The timing of decisions provides further insights into the treatment-specific unraveling process.

1. Introduction

George Akerlof commented on car insurance policies with voluntary GPS tracking ("Black Box") that were new at the time[1]:

"It will be interesting to see what will happen. ... When the black box becomes more widespread, it will be mainly those drivers who drive carefully anyway who will buy one. They hope to be able to lower their insurance premiums. The others will continue to drive without a box. Insurance for cars without a black box will become more and more expensive because the insurance companies know that they tend to be the worse risks. People who don't want to buy a black box ... may eventually no longer be able to get car insurance at all."

The quote succinctly summarizes the logic behind the information unraveling process as it is presented in the theoretical literature (Viscusi, 1978; Grossman and Hart, 1980; Grossman, 1981; Milgrom, 1981; Milgrom and Roberts, 1986). Privately informed players will fully and voluntarily disclose verifiable information. In a (hypothetical) dynamic reasoning process, initially only some senders,

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[1] Akerlof quoted and paraphrased in "Revolution in der KfZ Versicherung," Frankfurter Allgemeine Zeitung, 13/01/2014, https://www.faz.net/-ht4-7l81d, last retrieved 04 March 2025.

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namely those with the most favorable information, have an incentive to reveal their private information. As these players reveal, others will find it profitable to reveal, making it profitable for even more players to reveal, and so on. In the end, only the players with the least favorable information continue to conceal their private information. Since the concealing players are identified by the fact that they do not disclose, information unraveling is complete. With common knowledge of rationality, players anticipate the outcome of this thought process and immediately reveal their information in the one-shot game.

A growing number of experimental papers take models with information unraveling to the lab (Benndorf et al., 2015; Benndorf, 2018; Hagenbach and Perez-Richet, 2018; Penczynski and Zhang, 2018; Jin et al., 2021).[2] A common theme connecting these papers is that, by and large, information unraveling is incomplete (see Section 2 for a review of this work). Senders do not fully disclose information, and it is not just the players with the least favorable information who choose to conceal. Does the simultaneous-move setup overburden players and preclude complete unraveling? Or are there other features of the disclosure game that limit unraveling?

Limited depth of reasoning can explain incomplete revelation by senders. A level-k model (Nagel, 1995; Stahl and Wilson, 1995) matches the behavioral patterns in information unraveling experiments (see Benndorf et al., 2015). The revelation decisions of players with favorable information require little or no high-level reasoning about the decisions of others. Since players with less favorable information (who in theory should still reveal) must anticipate the behavior of others at higher levels of reasoning, they are more likely to conceal their information. After all, revelation is profitable for them only conditional on players with favorable information revealing. In Benndorf et al. (2015), we find that the more steps of reasoning players have to go through, the less likely they are to reveal.

To understand the role of limited depth of reasoning for incomplete unraveling, we start from the hypothesis that incomplete revelation is due to level-k reasoning and construct treatments that should increase unraveling according to the level-k model. The underlying game is a simple complete-information game framed in a labor market context. The players are referred to as workers who are heterogeneous with respect to their productivity. The workers need to decide whether to reveal their productivity to the employers. Revelation of the productivity is costly to the worker whereas not revealing (concealing) the productivity is free of charge. The employers are not modeled as human players, but we use the following payoff function for the workers that reflects a competitive labor market: Workers who reveal receive a wage equal to their productivity minus the cost of revelation, and workers who do not disclose receive a wage equal to the average productivity of all workers who do not reveal their productivity. Thus, the decision to reveal affects the wage paid to all workers who conceal.[3] We modify the design of this revelation game with two treatment variables, both of which are suitable for reducing the demands on subjects' level-k reasoning. First, we introduce a variant in which decision-making is essentially sequential and compare the behavior to a baseline setting with simultaneous moves. Second, we vary the cost of disclosure in two levels, resulting in a 2×2 treatment design.[4]

Regarding our first treatment variable (simultaneous vs. sequential moves), we introduce a novel treatment where decision-making mimics sequential moves. In these quasi-sequential treatments, participants have five minutes to decide, and during this time they see the current decisions of the other participants on their computer screen. They can change their decision at any point in time and as often as they want. Only the final decisions at the end of the experiment count. Any strategic uncertainty is eliminated by extending the clock if last-second changes are made. Thus, subjects do not need to anticipate the decisions of others. Also, the treatment makes it easier to find the optimal strategy, since the returns to revealing or not revealing are indicated on the screen. The decision to reveal information therefore boils down to a comparison of the two payoffs resulting from revealing and concealing. In terms of the level-k model, senders do not need to reason at higher levels at all.[5] In fact, decision-making in quasi-sequential designs more closely resembles the slow, step-by-step process that Akerlof describes than the simultaneous-move, one-shot game that the theory analyzes. However, the primary purpose of the new design is not to improve realism, but to eliminate strategic uncertainty.[6]

Our second treatment variable (high vs. low disclosure costs) also addresses the question of why complete unraveling is rarely observed. Quasi-sequential decision-making will not induce full disclosure if players stop the information unraveling process by concealing. If a worker with a high productivity does not reveal in our treatment with high disclosure costs, workers with lower productivity levels best respond by not revealing either, and the unraveling process comes to a halt. In the level-k model, $k = 0$ players are assumed to behave non-strategically, so they might conceal and thus interrupt the disclosure process altogether. To counter this possibility, we introduce treatments with low disclosure costs. In these treatments, more than one player in the group has an incentive to reveal for most strategy profiles. Some players' decisions still depend on other players' revelation decisions, but it is no longer the case that a single non-strategic $k = 0$ player can stop the revelation process.

We contrast the prediction of the unique Nash equilibrium (all workers except for those with the lowest productivity reveal) with a prediction based on level-k reasoning. This prediction is based on the smallest number of reasoning steps – the minimum

[2] Decision-making in these experiments corresponds to the simultaneous-move setup of the theory. In Jin et al. (2021); Penczynski and Zhang (2018); Hagenbach and Perez-Richet (2018), decisions are taken simultaneously and with random rematching after each round. Benndorf et al. (2015); Benndorf (2018) have simultaneous moves with fixed matching. Neither design corresponds to the quasi-sequential decision-making we introduce in this paper.

[3] If receivers (insurance companies or employers) are unaware that senders (drivers or workers) hold private information (Dye, 1985), this can impede full disclosure. In our setup, this is excluded by design.

[4] In our previous work (Benndorf et al., 2015), we investigate treatments for which complete, partial, or no revelation is predicted in Nash equilibrium by varying the set of possible productivities. In contrast, in this study we analyze how different revelation costs can affect the disclosure rate in a game where full disclosure is predicted.

[5] The treatment reduces the strategic complexity by removing the need for contingent reasoning. We do not claim that the level-k model is the only way to capture this, but it represents a parsimonious way to organize the data.

[6] Decisions that are actually sequential require an extensive-form game with a fixed order of moves. In our quasi-sequential design, players can coordinate without such an exogenous sequence of moves, and payoffs materialize only once, at the end of a five-minute period.

k-level – that players must take in order to reveal. The minimum k-level required for all players to reveal in a treatment suggests that quasi-sequential decision-making will lead to more information revelation, as will a reduction of the revelation cost.

While the prediction of the level-k model is a useful framework for interpreting our treatment effects, it does not take into account the empirical distribution of k-levels and cannot provide quantitative predictions. For this reason, we go one step further and calibrate the model. Based on the empirical distribution of k-levels observed in a similar game in a published data set, the calibration provides quantitative predictions. It calculates for each possible outcome of the game how likely each specific worker is to play consistent with that outcome given the distribution of k-levels. This implies how likely each outcome is to occur. The calibration yields predictions about how often the Nash equilibrium outcome, or full revelation, occurs in each treatment as well as predictions for the average disclosure rates in the four treatments. The calibration also predicts the revelation rates of each worker in each treatment.

Our results are as follows. We find that both quasi-sequential decision-making and low disclosure costs increase disclosure rates. The treatment that combines quasi-sequential decision-making and low revelation costs leads to almost complete unraveling, with a 95% revelation rate. Regression analyzes confirm that both treatment variables have the predicted effect, where one of them is significant and the other weakly significant. This lends support to level-k reasoning as an explanation of partial unraveling. The data are also consistent with the three sets of predictions of the calibrated level-k model (frequency of Nash outcomes, treatment-level revelation rates, and workers' productivity-specific disclosure behavior). Additional evidence for the relevance of the level-k model comes from the timing of decisions. In the quasi-sequential treatments, the actual sequence of decisions we observe is consistent with the hypothesized disclosure process. In contrast, the timing of revelation decisions in the simultaneous treatments is less correlated with worker productivities.

Section 2 reviews the literature. Section 3 introduces the game and the experiment while Section 4 presents the predictions based on the level-k model. The experimental results are presented in Section 5, followed by the calibration and calibration results in Section 6. The timing of the decisions is analyzed in Section 7. Section 8 concludes.

2. Related literature

The literature on information revelation falls into three areas: signaling,[7] cheap talk,[8] and—our focus—the disclosure of verifiable information. Experiments on disclosure games build on an established body of theoretical works (Viscusi, 1978; Grossman and Hart, 1980; Grossman, 1981; Milgrom, 1981; Milgrom and Roberts, 1986). Milgrom and Roberts (1986) already suggested that buyers of a good with an uncertain product quality may not be sophisticated enough to understand that "no news is bad news" and that this may induce potentially more sophisticated firms (senders) to reveal only positive information.

The first experimental paper on verifiable information disclosure we are aware of is Forsythe et al. (1989). It studies "blind bidding" in the motion picture industry. In the experiment, sellers have private information about a good and decide whether to reveal this information to the buyers. Revelation costs are zero. Participants learn to reveal private information over 16 to 22 rounds of play, but revelation remains incomplete. Early evidence on unraveling also comes from Forsythe et al. (1999) which studies a revelation game where the disclosed information is correct but possibly vague. This improves efficiency relative to treatments without communication or with cheap talk.

In our previous work (Benndorf et al., 2015), informed players must decide whether to reveal their productivity to uninformed parties when the latter are not human subjects but automated computer moves and when disclosure is costly. We find that revelation rates are too low compared to the prediction. In the main variant of this study, we observe only slightly more than 50% revelation, compared to the prediction of 83.3%. While a different frame leads to ten percentage points more revelation, the data do not converge to full disclosure in any treatment. Benndorf (2018) uses the same setup as Benndorf et al. (2015), but includes human players as receivers. The study supports the previous results in that the disclosure rates are often too low compared to the predictions.

In a related study, Li and Schipper (1995) investigate the revelation of verifiable but potentially vague information by sellers. Unraveling arguments imply that sellers always disclose the true quality to the buyers. The experimental results display relatively high levels of reasoning and some learning of sellers over the rounds. In contrast to our setting, there is no strategic uncertainty since it is a single seller who decides on the revelation.

In the experiment of Jin et al. (2021), both parties are represented by human participants. Their research question is whether "no news is bad news," that is, whether receivers are sufficiently pessimistic about senders who choose not to disclose. It turns out that they are not. This insufficient pessimism reduces senders' incentives to reveal: Senders disclose favorable information, but withhold less favorable information. Feedback on the interactions helps players to reach the equilibrium.

[7] In signaling games, senders may signal private information with a distorted action (Spence, 1973), and equilibria may convey information to the receiver. Experiments in this area include Miller and Plott (1985); Cadsby et al. (1990, 1998); Brandts and Holt (1992, 1993); Cooper et al. (1997a,b); Potters and Van Winden (1996); Cooper and Kagel (2003); Kübler et al. (2008); Jeitschko and Normann (2012); Hao and Wang (2022).

[8] In games with cheap talk, players' messages incur no cost and have no direct payoff implications, see Crawford (1998) for an early survey. They can be broadly classified according to whether the communication serves to convey private information or whether it expresses intentions, promises or threats. In the literature on communication of private information via cheap-talk messages, building on Crawford and Sobel (1982) and recently surveyed by Blume et al. (2020), some players have private information that is relevant to the decisions made by others. Experimental analyzes include Dickhaut et al. (1995); Forsythe et al. (1999); Blume et al. (1998, 2001). Cai and Wang (2006) show that, with increasing preference differences, less information is transmitted from the senders and used by the receivers, and they use models of bounded rationality, including a level-k (as we do). Laboratory experiments in the second realm are often about cooperating in dilemma games (Isaac et al., 1988; Bochet et al., 2006; Andersson and Wengström, 2007; Bochet and Putterman, 2009; Fonseca and Normann, 2012; Oprea et al., 2014) or coordination games (Blume and Ortmann, 2007, for example). Dilemma experiments with cheap talk are surveyed by Balliet (2010). A recent study (Jiménez-Jiménez and Rodero Cosano, 2021) compares both dilemma and coordination games with cheap talk and contains further references.

Table 1
2×2 treatment design.

	Simultaneous moves	Sequential moves
Low cost	SimLC	SeqLC
High cost	SimHC	SeqHC

Penczynski and Zhang (2018) study information unraveling in a competitive setting. Even when receivers are not sophisticated, competition between informed senders should lead to information unraveling. They compare a competitive setting to a monopoly and find that buyers are not skeptical enough, especially in the competition treatment. A competitive setting is also explored in Ackfeld and Güth (2023) who extend the literature on information disclosure to the case where the information is privacy-sensitive. For a duopoly with behavior-based pricing, Heiny et al. (2020) find that consumers reveal their private data in about two thirds of cases, confirming that information revelation is incomplete. Güth et al. (2019) analyze the case of welfare-enhancing information revelation in an acquiring-a-company game in theory and experiment.

An experiment by Hagenbach and Perez-Richet (2018) investigates non-monotonic incentives whereas the aforementioned literature study situations where senders have monotonic incentives, that is, they prefer to be perceived as having higher productivity, better quality, etc. Their data are consistent with a non-equilibrium model based on the iterated elimination of obviously dominated strategies.

There are also field studies suggesting that information unraveling is incomplete. One example is the work by Luca and Smith (2013) who demonstrate that business colleges only publicize rankings in which they did well. For restaurants which may voluntarily post their hygiene standards, Bederson et al. (2018) find that disclosure rates increase the more positive the inspection outcome. Mathios (2000) study the Nutrition Labeling and Education Act and find that, before labeling became mandatory, all healthy (low fat) products had a nutrition label while unhealthy often did not. Frondel et al. (2020) find that house owners reduce offer prices only when the disclosure of energy efficiency information became mandatory, and that the effect is stronger for owners who did not disclose before it was mandatory.

3. Game, experimental design and procedures

3.1. The game

There are n players who we refer to as *workers*. Workers are heterogeneous with respect to their productivity $\theta_i \in \Theta$. Productivities are ordered such that $\theta_1 \geq \theta_2 \geq \cdots \geq \theta_n$, with at least one strict inequality. We use W1, W2, ..., Wn to label the workers. Worker Wi has a productivity level θ_i, so that W1 represents the most productive worker and Wn the least productive. Productivity levels and therefore payoffs are common knowledge. All workers have two actions, they can either *reveal* their productivity to a fictitious employer, or they can *conceal* it. The decision of worker Wi is denoted by I_i where $I_i = 1$ indicates revelation and $I_i = 0$ denotes concealment. Revealing involves a cost, c, whereas concealing is free.

Workers are paid according to the following payoff function

$$\pi_i = I_i\left[\theta_i - c\right] + (1 - I_i)\left[\frac{\theta_i + \sum_{j\neq i}(1 - I_j)\theta_j}{1 + \sum_{j\neq i}(1 - I_j)}\right]. \tag{1}$$

In words, workers who reveal ($I_i = 1$) receive their productivity as a wage payment minus the cost of revelation c. Workers who conceal ($I_i = 0$) receive the average productivity of all concealing workers (including themselves) as a wage payment but do not pay c. While these wages reflect a competitive market, we do not explicitly model employers. Therefore, this is a static game with complete information and the equilibrium concept is Nash equilibrium.

3.2. Treatments

Subjects play the revelation game and have five minutes to decide whether to reveal. During these five minutes, they can change their decision repeatedly.[9] Only the decision at the end of this period is relevant for the subjects' payoffs. The initial (default) decision is to conceal. In order to avoid surprise decision changes at the very end of the period, the decision period was extended by another 10 seconds if someone changed their decision in the last 10 seconds of the five-minute interval.

The parameters we used in the experiment are $n = 6$, and $\Theta = \{607, 582, 551, 510, 448, 200\}$, as in Market B of Benndorf et al. (2015). The six productivity parameters are assigned randomly without replacement to a group of six subjects.

We consider four treatments in a 2×2 design as described in Table 1. One dimension is the cost of revelation. In the high cost (HC) treatments, the cost of revelation is $c = 100$, while it is $c = 28$ in the low cost (LC) treatments. The other dimension varies the decision-making environment that is either simultaneous (Sim) or quasi-sequential (Seq).

[9] All experiments included a real-effort task which preceded the revelation game. This task was necessary for a treatment called Entitlement, and we included the task in all other treatments to ensure comparability. The Entitlement treatment as well as another treatment called Unaware both serve to investigate the role of other-regarding preferences for limited unraveling. They are briefly described in the Supplementary Online Material, and we report on them in an earlier version of this paper available at https://rationality-and-competition.de/wp-content/uploads/2023/01/354.pdf.

The treatments with simultaneous moves use an environment that corresponds to the normal-form game: Subjects learn the payoff function from the instructions (reproduced in the Supplementary Online Material), and they are informed about their own productivity and the set of possible productivities when they make their revelation decision. They do not receive any new information during the five minutes of the decision process. In summary, the Sim treatments implement a game with strategic uncertainty.

In the treatments with quasi-sequential decisions, subjects have all the information they have in the Sim treatments, but they additionally see the currently selected strategy profile of their group.[10] They also see the payoffs resulting from either of their actions implied by the current strategy profile. More precisely, subjects see a list of all six workers in their group (including themselves), the productivities of these workers, and the current revelation choice of each worker. See the instructions in the Supplementary Online Material appendix for a screenshot.[11] Decision-making is quasi-sequential: Whenever a worker changes the decision, this information is immediately relayed to all other participants in the group. This procedure effectively removes all strategic uncertainty, such that erroneous beliefs or miscoordination cannot play a role. Since subjects are also informed about the resulting profits, decision errors based on incorrect calculations can be ruled out. Only the final decision of every player counts for the payoffs.[12]

3.3. Procedures

The experiment was conducted at the DICELab at Düsseldorf university. Most participants were students, but there were also some university employees. We conducted a total of 14 sessions, each with 12 to 36 participants (that is, two to six groups of six). A total of 402 subjects participated in this study. The sessions were conducted between September 2015 and June 2018 as well as in June 2023 using z-Tree and ORSEE (Fischbacher, 2007; Greiner, 2015). Sessions lasted about 45 minutes and the average payment was 11.58 Euros, which includes a show-up fee of 2 Euros.

4. Predictions

4.1. Nash equilibrium

We first present the static Nash equilibrium of the game. In general, $I_1 \geq I_2 \geq \cdots \geq I_n = 0$ must hold in any Nash equilibrium, see Benndorf et al. (2015) for a proof. Which players reveal or conceal in equilibrium depends on the set of productivities $\Theta = \{\theta_1, \theta_2, \dots, \theta_n\}$ and the cost of revelation c. The worker with the lowest productivity has a strictly dominant strategy to conceal as long as $c > 0$. For both values of the cost parameter and for simultaneous and sequential moves, there is a unique Nash equilibrium where $I_1 = \cdots = I_5 = 1 > I_6 = 0$. (As mentioned, we set $n = 6$, $\Theta = \{607, 582, 551, 510, 448, 200\}$, and $c \in \{28, 100\}$ in the experiment.) That is, workers W1 to W5 reveal their information.

Let r_c^t be the proportion of workers W1 to W5 who reveal in treatment $t \in \{Sim, Seq\}$ (Simultaneous or Sequential) with cost $c \in \{HC, LC\}$. The Nash prediction is the same for all treatments which implies that revelation rates are equal:

$$r_{HC}^{Sim} = r_{HC}^{Seq} = r_{LC}^{Sim} = r_{LC}^{Seq} = 1.$$

Although the Nash equilibrium is identical across treatments, we expect to see treatment differences in the degree of unraveling as the cognitive requirements vary substantially.

4.2. Level-k model

We use a level-k model (Nagel, 1995; Stahl and Wilson, 1995) to derive treatment-specific predictions. For tractability, we assume that a worker with level $k > 0$ best responds to the belief that all other workers are level $k - 1$. The behavior of level $k = 0$ players is non-strategic, and they are typically assumed to either choose a default action (as in Arad and Rubinstein, 2012) or to choose randomly. We allow for both deterministic and random choices, that is, level $k = 0$ players reveal with probability $p_0 \in [0, 1]$.

4.2.1. The Sim treatments

We start with simultaneous decision-making. For the moment and to simplify the exposition, assume that level $k = 0$ players conceal, that is, $p_0 = 0$ (we will drop this assumption below). Consider treatment SimHC. A level $k = 1$ worker best responds to the belief that all other players are level $k = 0$. Since level $k = 0$ workers conceal, the expected payoff of a level $k = 1$ worker from concealing is independent of the productivity and reads:

$$\frac{1}{6}\sum_{i=1}^{6}\theta_i = 483.$$

[10] In the field, people may not observe the full decision vector of other players. However, they may be able to observe a subset of the decisions of others (such as colleagues and friends), which can serve as a proxy for the decisions made in the population. In smaller groups, people may even be able to observe the full set of decisions.

[11] In a more complex design, one could separate the observability of payoffs and decisions. However, using the information about worker productivity that we provide in the instructions, participants can infer which workers reveal from the payoff information anyway. As our goal was to make the mechanism as transparent as possible, we decided to provide both pieces of information.

[12] This differs from the choice protocol procedure introduced by Agranov et al. (2015) that captures all provisional choices over a certain time period. Which choice matters for payment is randomly determined, providing an incentive for players to make the best decision at any point in time.

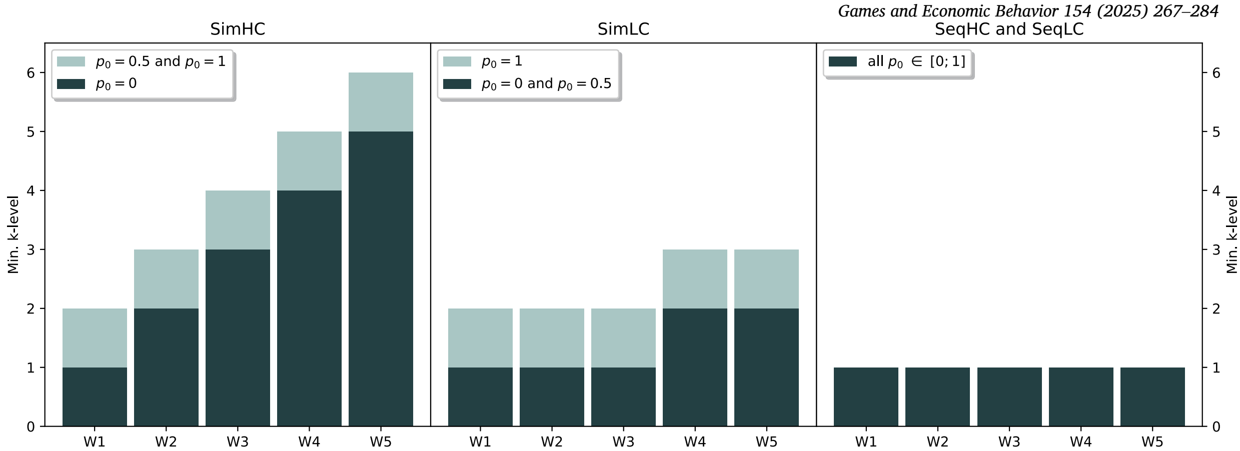

Fig. 1. Minimum level-k requirement for workers W1 to W5.

The payoff from revealing is $\theta_i - 100$, which is greater than 483 iff $\theta_i = \theta_1 = 607$. Thus, the best response is to reveal when the level $k = 1$ player is worker W1 and to conceal as worker Wj, $j > 1$. Next, a level $k = 2$ player believes that all other workers are level $k = 1$ and concludes that W1 reveals, and that all other workers conceal. The expected payoff for a level $k = 2$ worker Wi, $i > 1$ when concealing is:

$$\frac{1}{5}\sum_{i=2}^{6}\theta_i = 458.2.$$

A worker with level $k = 2$ reveals in the role of worker W2 since $\theta_2 - c = 582 - 100 > 458.2$ and conceals as worker W3 or higher (that is, when $\theta_i \le 551$). Worker W1 with level $k = 2$ would reveal as before. And so on: Our parameters in SimHC are chosen such that a worker Wi, $i \le 5$, reveals if and only if the level of reasoning is $k \ge i$.

Fig. 1 shows the specific minimum k levels required for workers to reveal in each treatment. The requirements in SimHC are shown in the left panel, and the dark bars are relevant when $p_0 = 0$. In that case, all workers with productivity $\theta_i, i \le 5$, reveal if and only if their k level is greater than their productivity level. Worker W6 (the one with the lowest productivity) never reveals for any $k > 0$ and is therefore excluded from the figure.

In the SimLC treatment, level $k = 1$ players reveal when they are workers W1, W2, or W3, and conceal otherwise. Why? Concealing yields 483 as above, but revealing now yields $\theta_i - 28$. For workers W1, W2, and W3, as shown in the middle panel of Fig. 1, we have that $\theta_i - 28 \ge 483$, see the dark bars. This demonstrates an important difference between SimHC and SimLC: The lower k-level required for unraveling results because the low cost makes it profitable for workers W2 and W3 to reveal regardless of the worker W1's decision. Similarly, workers W4 and W5 reveal if and only if they are at least level $k = 2$. If $k = 2$, W4 and W5 expect W1, W2, and W3 to reveal, and the remaining workers to conceal. The expected wage of workers W4 and W5 when concealing is therefore $(510 + 448 + 200)/3 = 386$. Since $\theta_4 - c = 510 - 28 = 482$ and $\theta_5 - c = 448 - 28 = 420$, the W4 and W5 will reveal for $k \ge 2$.

When we generalize the behavior of players of level $k = 0$ and allow their choices to be random, that is, when we allow for any $p_0 \in [0, 1]$, the minimum k-levels required to reveal are sensitive to the p_0 assumption. As the derivations are tedious and do not add any new insights, we relegate them to Appendix A.[13] The results for general p_0 are, however, straightforward to visualize. Fig. 1 shows how level $k = 0$ behavior affects minimum k levels for $p_0 = 0$, $p_0 = 0.5$, and $p_0 = 1$. The required k-levels for the Sim treatments are simply augmented by one for $p_0 = 1$. In Appendix A, we show that the treatments have different cutoffs of p_0 at which the required k-level changes, but all possible patterns fall within the range shown in Fig. 1. Fig. 8 in Appendix A presents the minimum k-levels for all $p_0 \in [0, 1]$.

4.2.2. The Seq treatments

The quasi-sequential decision (Seq) treatments are designed to reduce the level-k requirements as displayed in the right panel of Fig. 1. In SeqHC, worker W1 reveals as long as the level of reasoning is $k \ge 1$, as before. Now, worker W2 observes the decision of W1 and its payoff implication. Thus, W2 no longer needs to anticipate W1's behavior, but simply pick the most profitable action. The same reasoning applies to workers W3, W4 and W5. For all workers with productivity θ_i, $i \le 5$, $k = 1$ is sufficient to reveal.[14] The

[13] The $p_0 = 1$ case is counterintuitive but straightforward: If level $k = 1$ players best-respond to the belief that all other players reveal, they expect to be the only player who conceals if they decide to do so. If worker Wi conceals while all other workers Wj, $j \neq i$, reveal, Wi receives the productivity as a payoff, $\theta_i > \theta_i - c$. This holds for all Wi and implies that all players of level $k = 1$ conceal, regardless of their productivity. Next, workers of level $k = 2$ expect that all other players are of level $k = 1$ and concealing. But this means that they are in exactly the same situation as level $k = 1$ players when $p_0 = 0$. The minimum k-level required for disclosure is simply augmented by +1 when $p_0 = 1$ compared to $p_0 = 0$, see Fig. 1.

[14] In the Seq treatments, workers do not need to form beliefs about the behavior of others. They only need to respond to the current decision profile. However, we argue that a level of $k \ge 1$ is required for disclosure because $k = 0$ level players may conceal, as their choice is non-strategic.

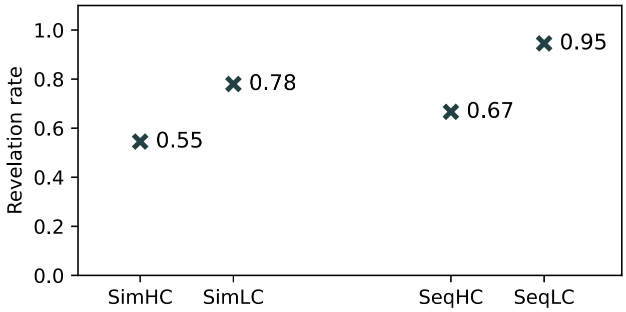

Fig. 2. Average revelation rates by treatment, using data from workers W1 to W5.

same holds for the sequential low-cost treatment (SeqLC). In contrast to the Sim treatments, the Seq treatments are invariant to the p_0 assumption: The requirement for optimal play is $k \geq 1$, independent of p_0, as detailed in Appendix A.

While workers in the Seq treatments do not need to reason at higher levels, the unraveling process can still be disrupted. In SeqHC, level $k = 0$ workers can stop the revelation process: If worker W1 is level $k = 0$ and conceals, no one in the group reveals. If worker W2 is level $k = 0$ and conceals but worker W1 is $k \geq 1$, only worker W1 reveals and the others conceal, and so on. In contrast, even if W1 conceals in SeqLC, the workers W2 and W3 still have an incentive to reveal provided they are $k \geq 1$: Revealing yields $\theta_2 - c = 582 - 28 = 574$ and $\theta_3 - c = 551 - 28 = 523$ whereas concealing yields just $\sum_{i=2}^{6} \theta_i / 5 = 458.2$. Thus, if there are workers with level $k = 0$ who conceal, we expect more unraveling in SeqLC than in SeqHC.

4.2.3. *Predicted treatment effects*

To summarize, we expect both the lower cost and the quasi-sequential decision-making treatments to increase disclosure rates. Based on the minimum k-level necessary such that all workers disclose (see Fig. 1), we conclude that $r_c^{Sim} < r_c^{Seq}$, $c \in \{LC, HC\}$, also considering that workers with level $k = 0$ are less likely to stop the unraveling process in SeqLC. Moreover, we expect that $r^t_{HC} < r^t_{LC}$, $t \in \{Sim, Seq\}$.

Prediction. *Based on the minimum k-levels required for revelation, we expect more information disclosure in the Seq compared to the Sim treatments and in the LC compared to the HC treatments.*

5. Results

5.1. *Data*

Our subjects interact in groups of six. Depending on the treatment, we have observations from 10 (SimLC), 11 (SimHC, SeqLC), and 12 (SeqHC) groups. Since subjects engage in one-shot interactions, we collected between 60 and 72 reveal/conceal decisions per treatment. Observations within groups are not independent in the Seq treatments, so we report bootstrapped (1,000 repetitions) standard errors clustered at the group level, and we reduce the data obtained in a group to a single observation when running nonparametric tests.[15] We report significant (weakly significant) results when $p < 0.05$ ($p < 0.1$), based on two-sided p-values.

5.2. *Nash equilibrium outcomes*

We begin by reporting on the frequency with which the Nash equilibrium profile, that is, full disclosure ($I_1 = \cdots = I_5 = 1 > I_6 = 0$), occurs. The Nash outcome occurs most frequently in SeqLC (73%), followed by SeqHC (42%) and SimLC (30%). In SimHC, there is not a single Nash equilibrium outcome (0%). That is, not only is the Nash outcome rare, but its frequency also strongly differs between treatments—in violation of the Nash prediction.

We proceed to assess the statistical significance of these findings by coding each group outcome as “Nash” or “other” and applying Fisher’s exact test. The results reveal a statistically significant variation in the proportion of Nash outcomes across the four treatments (4×2 Fisher exact, $p = 0.003$). For the pairwise comparisons that are plausible within the 2×2 design, we identify a significant difference between SimHC and SeqHC (2×2 Fisher exact, $p = 0.037$), and weakly significant differences between SimHC and SimLC ($p = 0.090$) and SeqLC and SeqHC ($p = 0.086$). The difference from the pairwise comparison between SeqHC and SimHC does not reach statistical significance.

[15] There is no interaction in the Sim treatments, so clustering at the subject level (or using each individual observation) would be plausible. If we do this in the Sim treatments, the results would change only slightly with respect to moderately lower p values.

Table 2
Linear probability models of decisions to reveal.

	(1)	(2)
HC	-0.258***	-0.235***
	(0.0746)	(0.0905)
Seq	0.142*	0.165**
	(0.0778)	(0.0679)
SeqHC		-0.0442
		(0.156)
Constant	0.792***	0.780***
	(0.0568)	(0.0610)
Obs.	220	220
R^2	0.110	0.111

Data from workers W1 to W5, all treatments, bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Result 1: *The Nash equilibrium prediction (workers W1 to W5 reveal, worker W6 conceals) does not match the experimental results. Full disclosure is rarely achieved and its proportion varies significantly across treatments—from 0% (SimHC) to 73% (SeqLC).*

5.3. Revelation rates

Our main result is shown in Fig. 2 which displays the disclosure rates across treatments.[16] Both treatment variations, Seq and LC, increase revelation, as expected. Notably, we see almost complete (95%) revelation in SeqLC. This is in contrast to the much lower disclosure rates for the other treatments. The SimHC treatment has a revelation rate of 55% which replicates the results of Benndorf et al. (2015) where the average was 53% when using a loaded frame as in this experiment, despite some differences in the design.

Table 2 presents the results of linear probability models of the individual decision to reveal. We use the treatments HC and Seq, and the interaction Seq × HC as explanatory variables, such that the constant reflects SimLC. Model (1) confirms that both treatment variables have an impact: Subjects are significantly less likely to reveal if the cost of revelation is high, and they are (weakly) significantly more likely to reveal in the environment with quasi-sequential decision-making, confirming our expectations. The interaction term Seq × HC in (2) is negative but insignificant, indicating a negligible additional effect on revelation behavior when combining quasi-sequential moves with high costs. A post-hoc Wald test following regression (2) indicates that SimHC and SeqHC do not differ significantly.

Non-parametric tests yield a similar picture. The revelation decisions are significantly different across treatments according to an omnibus test (Kruskal-Wallis, $p = 0.002$). Turning to pairwise comparisons within the 2×2 design, we find significant differences between $r^{Sim}_{HC} < r^{Sim}_{LC}$ (Mann-Whitney U, $p = 0.024$) and $r^{Sim}_{LC} < r^{Seq}_{LC}$ ($p = 0.030$). The comparison of r^{Seq}_{HC} and r^{Seq}_{LC} yields a weakly significant difference ($p = 0.068$). The comparison between SeqHC and SimHC is not significant. We summarize these findings in:

Result 2: *Low disclosure costs significantly and quasi-sequential moves weakly significantly contribute to more revelation, as predicted. Pairwise comparisons of treatments are also (weakly) significant, except that at high costs, there is no significant effect of the timing of moves on revelation rates.*

5.4. Workers' productivity-specific revelation rates

Fig. 3 shows that the workers' productivity-specific revelation rates vary widely. While workers W6 always conceal, we see that the revelation rates of workers W1 to W5 differ from each other in all treatments except SeqLC, with a negative correlation between productivity and revelation behavior.

To assess the statistical significance of productivity for revelation choices, Table 3 presents linear regressions with the reveal decisions of workers W1 to W5 as the dependent variable and the cardinal integer variable *Productivity*, coded from 1 to 5, as the only explanatory variable. The impact of the *Productivity* is significant in all treatments except SeqLC, and its effect is strongest in SimHC.

Result 3: *The revelation rates of workers of different productivities differ within and across treatments. They are significantly negatively correlated with the workers' productivity level, except in SeqLC.*

[16] We exclude worker W6 from the calculation of the aggregate (treatment-level) disclosure rates as well as from the regression analyzes in Tables 2 and 3. The reason is that concealing is a strictly dominant strategy, and all workers W6 in our dataset actually concealed. Thus, their decisions do not yield any insights regarding treatment effects. Including worker W6 in Table 3 would also exaggerate the effect of *Productivity* in the regressions.

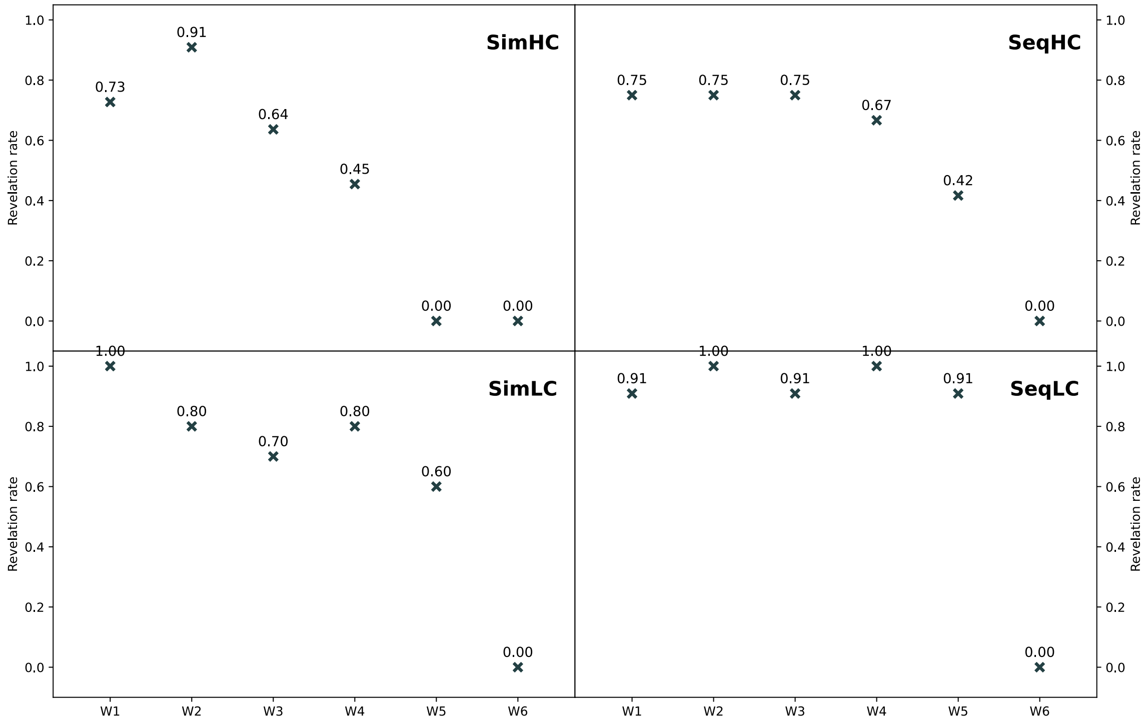

Fig. 3. Workers' productivity-specific revelation rates by treatment, using data from all workers.

We can relate the finding of a negative correlation of disclosure behavior with productivity to the minimum k-levels for each worker Wi in Fig. 1. According to level-k reasoning, we expect worker productivity to have a negative effect on revelation in the Sim, but not in the Seq treatments. This is due to the fact that minimum k-levels increase in worker productivity when moves are simultaneous, but they are flat (equal to one) when moves are quasi-sequential. Thus, the regressions in Table 3 are consistent with the individual level minimum k-level analysis for SimLC, SimHC, and SeqLC. The only exception is for SeqHC, where the minimum k-level is 1 for all workers, but we observe a significant correlation with worker productivity, see Table 3. We will be able to address this using the calibrated level-k model.

Table 3
The impact of workers' productivity on decisions to reveal, by treatment.

	SimHC	SimLC	SeqHC	SeqLC
Productivity	-0.191***	-0.080**	-0.075**	0.000
	(0.0237)	(0.0311)	(0.0312)	(0.0262)
Constant	1.118***	1.020***	0.892***	0.945***
	(0.113)	(0.0772)	(0.157)	(0.0829)
Observations	55	50	60	55
R-squared	0.294	0.075	0.051	0.000

Data from workers W1 to W5, separated by treatment, bootstrapped standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1.

6. Calibration of the level-k model

6.1. Setup

Predictions about how many treatments or workers of different productivity levels differ depend on the empirical frequency of level-k workers have: For example, how much less revelation we see in SimHC than in SimLC depends on the frequency of $k > 3$ workers. For the calibration, we use the empirical distribution of k-levels observed in Benndorf et al. (2017) who used a variation of

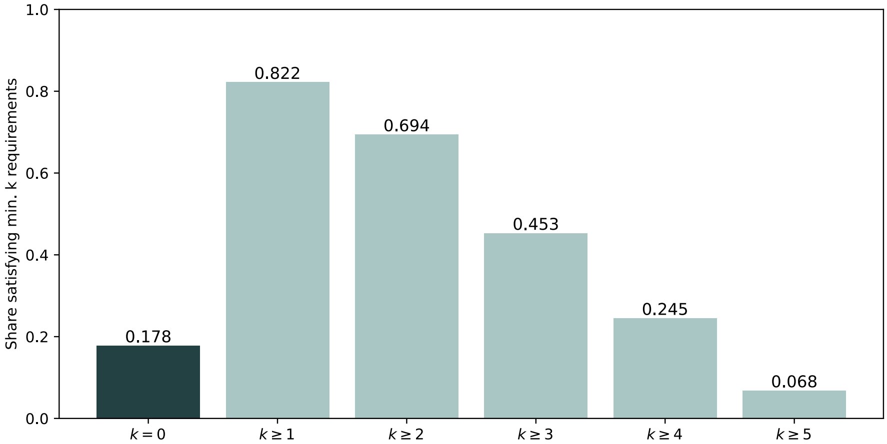

Fig. 4. Share of level $k = 0$ players and share of players who meet a given minimum k requirement, based on data from Benndorf et al. (2017).

the SimHC treatment to elicit subjects' k-levels.[17] Fig. 4 shows this distribution with the share of subjects who meet a given level-k requirement as well as the share of level $k = 0$ players.[18] We calibrate the model for all possible $k = 0$ assumptions, that is, we allow for any probability $p_0 \in [0, 1]$ that a $k = 0$ worker reveals.

The calibration yields, for each p_0 assumption, a point prediction for each worker W1 to W6, and these productivity-specific revelation rates are then aggregated to treatment-specific revelation rates. We run the calibration for all $p_0 \in \{0.00, 0.01, 0.02, ..., 1.00\}$. Allowing for the full range of behavior from $p_0 = 0$ (always conceal) to $p_0 = 1$ (always reveal) yields an interval for each prediction.

6.2. Calibrated share of Nash outcomes

We start with the likelihood of observing the Nash outcome ($I_1 = I_2 = I_3 = I_4 = I_5 = 1 > I_6 = 0$), assuming for the moment that $k = 0$ workers conceal ($p_0 = 0$). In the SimHC treatment, this occurs when worker W1 is $k \geq 1$, worker W2 is $k \geq 2$, worker W3 is $k \geq 3$, worker W4 is $k \geq 4$, worker W5 is $k \geq 5$, and worker W6 is $k \geq 0$. From the empirical distribution of the k levels in Fig. 4, the probability of this outcome is $Prob(k \geq 1) \cdot Prob(k \geq 2) \cdot Prob(k \geq 3) \cdot Prob(k \geq 4) \cdot Prob(k \geq 5) \cdot Prob(k \geq 0) = 0.822 \cdot 0.694 \cdot 0.453 \cdot 0.245 \cdot 0.068 \cdot 1 \approx 0.4\%$. In SimLC, the corresponding expression is $Prob(k \geq 1) \cdot Prob(k \geq 1) \cdot Prob(k \geq 1) \cdot Prob(k \geq 2) \cdot Prob(k \geq 2) \cdot Prob(k \geq 0) = 0.822^3 \cdot 0.694^2 \cdot 1 \approx 26.8\%$. In the quasi-sequential treatments, $Prob(k \geq 1)^5 \cdot Prob(k \geq 0) = 0.822^5 \cdot 1 \approx 37.5\%$ holds for both SeqHC and SeqLC.

When we allow for any $k = 0$ assumption ($p_0 \in [0, 1]$), the calibration of the share of Nash outcomes is more involved. We only provide a rough sketch here while Appendix A describes the details. In the Sim treatments, the calibration follows the same logic as with $p_0 = 0$, but we have to take into account that a worker could also reveal with level $k = 0$. So, worker W6 does not necessarily conceal, but only with probability $0.178 \cdot (1 - p_0) + Prob(k \geq 1)$. The workers W1 to W5 now reveal with probability $0.178 \cdot p_0 + Prob(k \geq k_{min})$. The probability of observing the Nash outcome is then the product of all the individual probabilities. The calibration of the frequency of Nash outcomes for the quasi-sequential treatments and any $p_0 \in [0, 1]$ is more straightforward. Here, we only need to consider whether or not a player reasons at $k > 0$, but the calibration still depends on the assumption for level $k = 0$ play. For the Nash outcome, we get the following probabilities: Worker W6 will conceal with probability $0.178 \cdot (1 - p_0) + 0.822$ and the probability that one of the workers W1 to W5 will behave according to the Nash profile is $0.178 \cdot p_0 + 0.822$. The probability of observing the Nash outcome is again the product of all the individual probabilities. Conspicuously, the predicted frequency of the Nash outcome does not depend on the cost parameter in the Seq treatments, but this is a peculiarity of the Nash profile and does not generally apply to all strategy profiles.

The left panel of Fig. 5 shows the results of the calibration exercise. We display the predicted intervals (shaded areas) and the outcomes observed in the experiments (dark markers). All four treatment means are within the calibrated interval, even for the small interval of SimHC. Put differently, for each of the four shares of Nash outcomes, we can find a p_0 that rationalizes the data.

6.3. Calibrated revelation rates

We first calibrate the revelation rates for each treatment. To obtain these predictions, we repeat the above analysis of the Nash equilibrium profile for all 64 possible pure-strategy profiles. We then use the predicted probabilities of observing the individual

[17] The participants in Benndorf et al. (2017) played SimHC using the strategy method where every subject had to make a decision for each worker W1 to W6. The strategy method elicits an exact k-level for each subject. The distribution of k-levels is not significantly different from the distribution observed in Arad and Rubinstein's (2012) baseline treatment.

[18] Assigning levels greater than three to players is consistent with a literal interpretation of our model. However, Bosch-Domenech et al. (2002) argue that participants skip such high levels of reasoning and instead arrive at Nash equilibrium play.

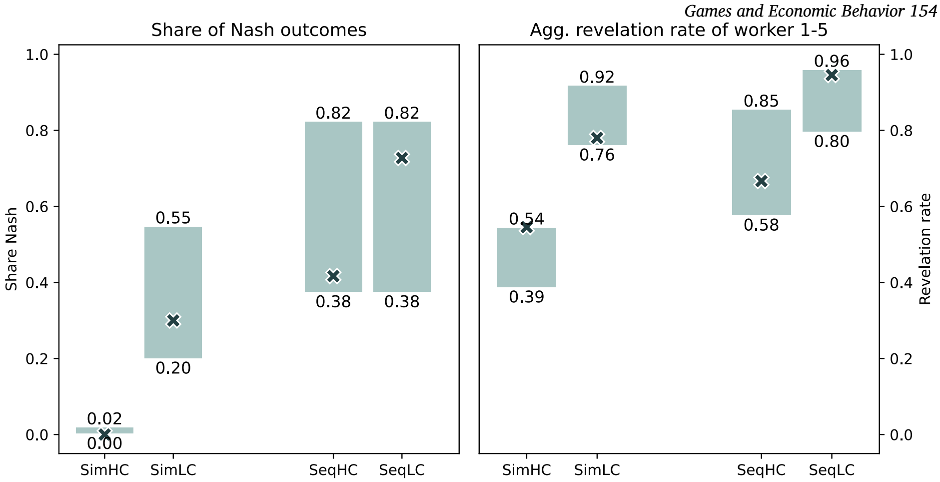

Fig. 5. Calibrated and observed frequency of the Nash equilibrium outcome, by treatment (left panel); calibrated and observed aggregate revelation rates of workers W1 to W5, by treatment (right panel).

strategy profiles to compute the expected revelation rates for a given treatment or for individual workers in a given treatment. See Appendix A for further details.

The calibrated treatment-level revelation rates are shown in the right panel of Fig. 5. The boxes indicate the interval implied by the calibration. The intervals contain the treatment averages (indicated by crosses) in all treatments except for SimHC which is just off the mark (55% vs. 54%).

The calibration suggests a ranking of our treatments regarding the revelation rates. While there is some overlap of the intervals, it holds that $r^{Sim}_{HC} < (r^{Seq}_{HC} \gtreqless r^{Sim}_{LC}) < r^{Seq}_{LC}$ for all $p_0 \in [0,1]$, and the strict ranking $r^{Sim}_{HC} < r^{Seq}_{HC} < r^{Sim}_{LC} < r^{Seq}_{LC}$ emerges for all $p_0 < 0.915$, which is also the ranking observed in the data. This result is statistically significant, since we observe the one predicted ranking out of $4! = 24$ possible rankings ($p = 1/24 = 0.042$).

We now turn to the workers' productivity-specific revelation rates, depicted in the four panels of Fig. 6.[19] Although a few of the observed average revelation rates, indicated by the crosses, lie outside of the calibrated range, the fit appears to be relatively good. In particular, the calibration suggests that there is a correlation of productivity and average revelation in SeqHC, which is significant in the regressions reported in Table 3, but which is inconsistent with the minimum k-levels that are constant at $k \geq 1$, see Fig. 1. In SimHC the data matches the calibrated interval only for worker W6, but the calibration suggests a picture that is qualitatively similar to the data.

6.4. *Predictive power of the calibrated model*

How accurate is the calibration? We consider two approaches. First, we relate the probability of success of the prediction to the probability of success by chance (Cohen, 1960). The second approach measures the distance between the data and the prediction.

We start with the relative probabilities of success, Cohen's κ. Take the frequency of Nash outcomes in Fig. 5. The probability that completely random data (a number between zero and one, uniformly distributed) is within the calibrated interval is $0.02 - 0.00 = 0.02$ for SimHC, $0.55 - 0.2 = 0.35$ for SimLC, and $0.82 - 0.38 = 0.44$ for both Seq treatments. The average probability of success of a random classification is therefore $P^C = 0.313$. Since the actual probability of success is $P^0 = 1.00$, we get $\kappa = (P^0 - P^C)/(1 - P^C) = 1.00$ (Cohen, 1960), indicating a perfect classification in this case. Put differently, given the random success probabilities, the exact probability that four out of four trials are successful is $p = 0.001$. Thus, we can reject the null hypothesis that success is random. Proceeding in the same way with the average revelation rates of the treatments in the right panel of Fig. 5, we find $P^C = 0.185$ and an actual success rate $P^0 = 0.75$, suggesting $\kappa = 0.693$, indicating a substantial relative success rate. Given the random success probabilities, the probability of obtaining three or more successes $p = 0.021$, again rejecting that success is random. Finally, consider the workers' productivity-specific data in the four panels of Fig. 6. Taking the 24 calibrated intervals together, we get a more moderate $\kappa = (0.542 - 0.195)/(1 - 0.195) = 0.430$. The size of our calibrated intervals would suggest a total of 4.69 random hits whereas in the figure, we find 13 hits. While calculating the exact probabilities is computationally infeasible here, using a binomial test with the average success probability across the 24 intervals in suggests that the probability of at least 13 out of 24 is $p < 0.001$.

[19] The calibration of the disclosure rate of worker W5 is based on the assumption that 50% of the $k \geq 5$ players are also $k \geq 6$. The reason why we need to impose this assumption is that the SimHC game used by Benndorf et al. (2017) to elicit k-levels does not allow for the elicitation of k-levels greater than five while some p_0 assumptions call for a k-level of six when worker W5 reveals. To account for this, we need to make an assumption on how many players with $k \geq 5$ are also $k \geq 6$. Comparing the two extreme cases (all of them or none of them are $k \geq 6$), we find that the lower bound of the aggregate revelation rate in SimHC is between 0.38 and 0.39, and that the upper bound of the revelation rate of worker W5 is between 0.18 and 0.25.

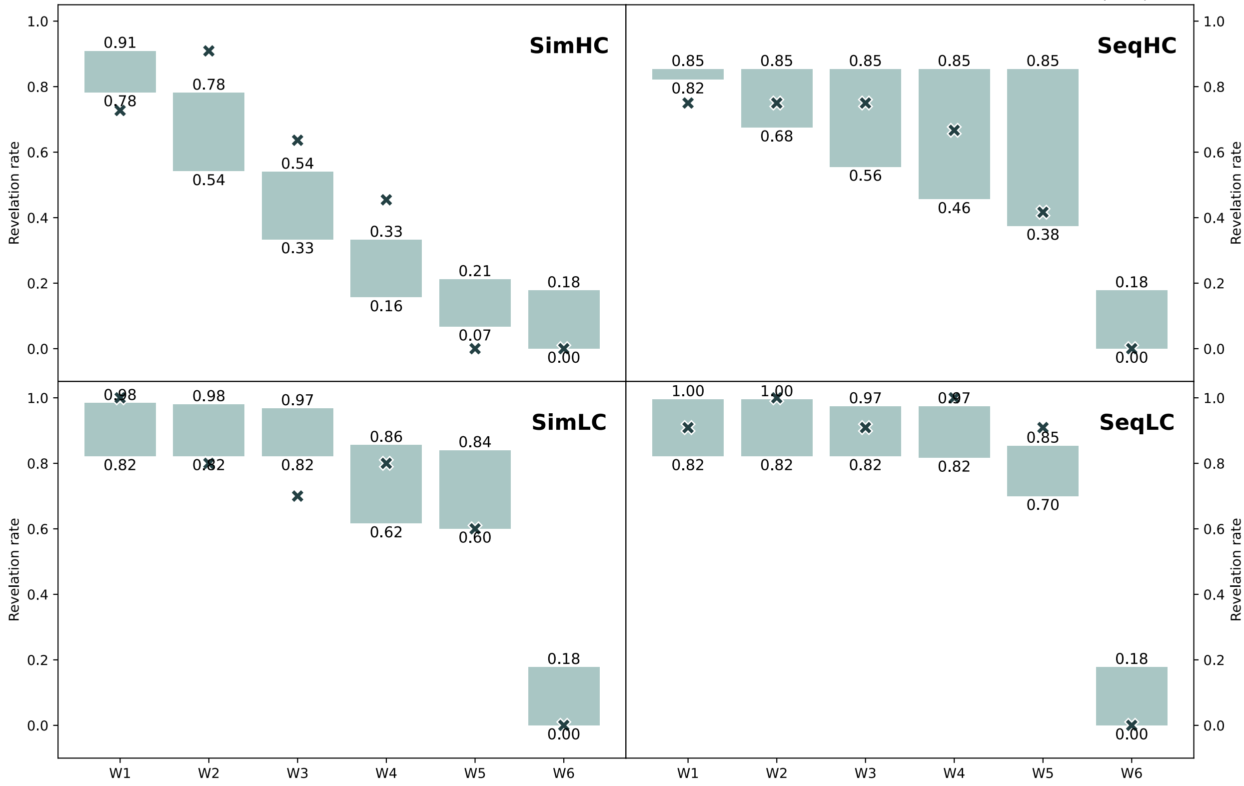

Fig. 6. Calibration results (boxes) and data (crosses), workers' productivity-specific revelation rates by treatment, using data from workers W1 to W6.

This leads us to the motivation for our second measure: Even when the data are outside the calibrated intervals, the gap is typically not substantial and the observed rates often only barely miss the interval bounds. To quantify this, we regress the experimental observations on the predictions with univariate regressions of the form

$$\textit{Observation}_i = \beta_0 + \beta_1 \cdot \textit{Prediction}_i + \epsilon_i.$$

We include all data points reported in Figs. 5 and 6: The left-hand side of the regression contains the observations from the four observed shares of Nash outcomes (one for each treatment), the four observed treatment-level revelation rates, and the 24 observed individual revelation rates of the workers with different productivities (six for each of the four treatments). The *Prediction* variable on the right-hand side is treated analogously: For each data point, we have one predictor. To take into account the full range of $k = 0$ behaviors, we run the regression for 101 different values of p_0, $p_0 \in \{0.00, 0.01, ..., 1.00\}$. This results in 101 estimates of the constant β_0 and the coefficient β_1. For any model that predicted perfectly, we would see $\beta_0 = 0$ and $\beta_1 = 1$ and the corresponding standard errors would be zero. Empirically, we expect β_0 not to differ significantly from zero. If so, this would suggest that the calibrated level-k model never systematically under- or overestimates the observed revelation rates and frequency of Nash outcomes. If β_1 differs statistically from zero, this would imply the decisions are correlated with the prediction. If a β_1 coefficient is not statistically different from one, this would further support the model in that linear transformations of the models' predictions do not outperform the plain prediction for $\beta_1 = 1$. The regression results reveal that the constant β_0 is never significantly different from zero. The coefficient β_1 always differs from zero and is never significantly different from one.[20] Altogether, we interpret these results as evidence that the calibrated level-k model explains the experimental data well.

Result 4: *The calibrated level-k model predicts the frequency of Nash outcomes as well as the revelation rates of each treatment and each worker W1 to W6 significantly better than random, and we cannot detect any significant biases in the predictions.*

[20] The p-values of the 101 β_0 coefficients all suggest $\beta_0 \neq 0$ at $p > 0.138$. For the 101 β_1 estimates, we obtain $\beta_1 \neq 0$, all at $p < 0.001$. Post-estimation Wald tests show that the β_1 coefficients never differ significantly from one (all $p > 0.313$).

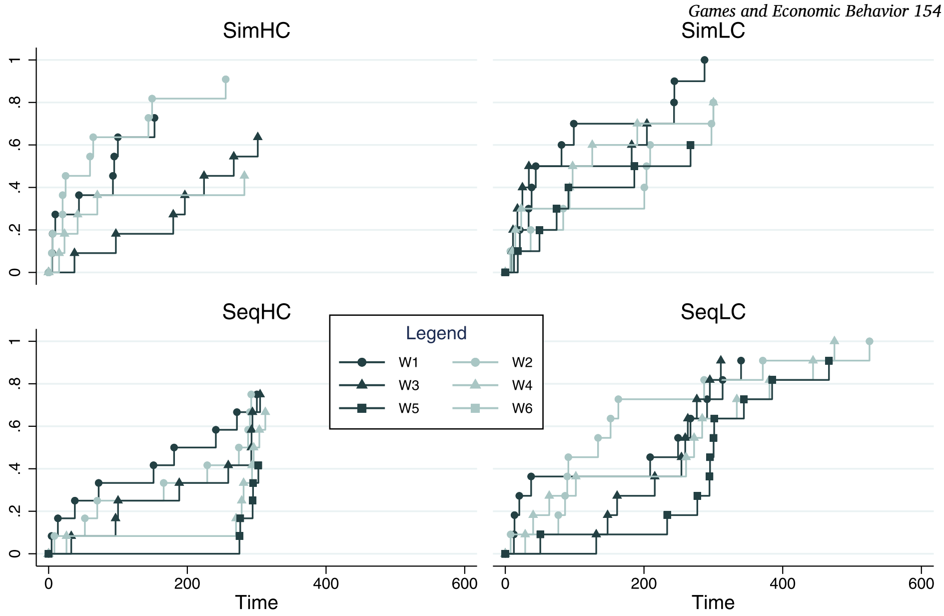

Fig. 7. The percentage of workers who have made their final decision to reveal at a given point in time (in seconds).

7. Timing of decisions

Central to the notion of information disclosure is a hypothetical or actual sequence of moves: Initially, only those with the most favorable information have an incentive to reveal their private information. Conditional on these players revealing, others will find it profitable to reveal, making it profitable for even more players to reveal, and so on. Since we can observe the sequence of decisions in our experiment, this provides additional insights into the process of information disclosure.

Fig. 7 shows at what point in time subjects make their *final* disclosure decision. Recall that players have five minutes to make their decision, allowing them to switch between revealing and concealing, with only their final decision affecting their payoffs. In Fig. 7, the horizontal axes show the time that has elapsed (in seconds), and the vertical axes show the proportion of subjects who have already made their final decision to reveal. In other words, each graph looks at the subjects who reveal at the end of the experiment and shows at what point they stopped changing their strategy. The endpoints correspond to the workers' productivity-specific revelation rates reported in Fig. 3.

Fig. 7 yields a number of insights. In the quasi-sequential treatments, the hypothetical dynamics are in line with the observed sequence of decisions. For SeqHC, this means that worker W1 reveals first, followed by W2, followed by W3, and so on. Interestingly, workers W4 and W5 do not make their final reveal decision until the very end of the experiment. In comparison, in SeqLC the hypothetical dynamics only suggest that worker W4 should reveal if at least one of the three workers with higher productivity reveals, and that worker W5 will not reveal unless at least three other workers reveal. This is consistent with the results shown in the figure. Unlike in SeqHC, worker W1's disclosure is followed by W4 disclosing while W2 and W3 follow somewhat later. W5 is the last to make the reveal decision. For SimHC and SimLC, the patterns are not as clear, with W2 and W3, respectively, taking the lead and revealing their productivity. This is to be expected, as subjects in these treatments cannot observe the decisions of their peers.

In a second step, we analyze who changes the action conditional on the decision profile displayed on the screen, focusing on the six profiles of the Seq treatments that are monotonic. A decision profile is monotonic if workers Wj, $j = 2, \ldots, 5$ reveal only if all workers with higher a productivity Wi, $i < j$ reveal. The monotonicity property makes these profiles interesting in terms of the unraveling process. The Supplementary Online Material contains tables with all profiles reached in the two Seq treatments. In Table 4, the profiles are labeled according to the actions taken by workers with different productivities. For example, profile 110000 refers to the case where workers W1 and W2 reveal while the remaining workers conceal. The second column shows the average total time a profile was displayed on the screen in each group, and the third column documents how often an average group reached the profile during the decision process. Columns labeled "W1" to "W6" show the proportion of cases where a particular worker Wi changed their strategy when reaching the profile, with numbers in boldface indicating that the worker has an incentive to switch. The last column shows the cases where no worker changed their strategy (that is, when the profile was the final one reached at the end of the decision phase).

The top part of Table 4 shows the data for SeqHC. Profile 000000 is the default at the beginning, but it also reappears later, on average 3.3 times in each group. In about 56% of all cases, the subject who changes the action in this profile is worker W1. This is consistent with the hypothetical unraveling process, as worker W1 is the only player who has an incentive to change the action in profile 000000. In profile 100000, worker W2 is the only one who has an incentive to change the action, and it is this worker who responds by switching to reveal in 53% of all cases. This pattern continues for the following profiles. In HC, there is always exactly

Table 4
The table shows, for the monotonic strategy profiles, the average duration ("time") and the number of times these profiles appear on the screen ("count"). It then shows the frequencies of workers changing their action at the given profile ("W1" ... "W6"), where the last column refers to cases where no worker changed their action ("no switch"). Entries in boldface indicate that workers have an incentive to change their action for the given profile.

			SeqHC						
	On screen		Which worker reacts						
Profile	time	count	W1	W2	W3	W4	W5	W6	No switch
000000	44.5	3.3	**0.56**	0.18	0.12	0	0.06	0.04	0.04
100000	25.9	2.7	0.20	**0.53**	0.08	0.07	0.12	0.00	0.00
110000	34.6	2.7	0.19	0.03	**0.61**	0.05	0.13	0.00	0.00
111000	30.1	2.9	0.03	0.02	0.25	**0.55**	0.12	0.00	0.03
111100	51.6	3.6	0.04	0.05	0.05	0.11	**0.53**	0.06	0.17
111110	84.1	4.4	0.03	0.06	0.04	0.28	0.35	0.10	0.15
			SeqLC						
	On screen		Which worker reacts						
Profile	time	count	W1	W2	W3	W4	W5	W6	No switch
000000	17.9	1.7	**0.29**	**0.30**	**0.23**	0.00	0.09	0.09	0.00
100000	5.0	2.0	0.35	**0.12**	**0.33**	**0.20**	0.00	0.00	0.00
110000	22.9	2.8	0.38	0.25	**0.13**	**0.25**	0.00	0.00	0.00
111000	15.9	5.0	0.24	0.26	0.06	**0.19**	**0.25**	0.01	0.00
111100	35.7	16.1	0.04	0.11	0.15	0.05	**0.61**	0.04	0.01
111110	70.3	14.1	0.06	0.04	0.04	0.05	0.31	0.21	0.28

one worker who should switch from concealment to revelation, and the table documents that this is always the most likely response to these profiles.

The patterns in SeqLC (the bottom part of the Table 4) also reflect the strategic properties of the game, which are somewhat more complex. In profile 000000, workers W1, W2, and W3 have an incentive to switch to revealing, and we observe these workers reveal with a likelihood of 29%, 30% and 23%, respectively. In the second row, workers W2, W3, and W4 have an incentive to change their action, and they do so with a probability of 12%, 33% and 20%, respectively. In the third row, workers W3 (19%) and W4 (25%) best respond by revealing. At the same time, it is evident that workers W1 and W2 sometimes switch back to concealing for profiles 110000, and 111000. These decisions are mostly overruled again later on, but they show the players' experimentation.

In general, the decision phase for SeqLC is more noisy than for SeqHC. This emerges from Table 4 and from Fig. 7 which shows that the decision phase in SeqLC tends to be longer than in the other treatments.[21] In spite of the seemingly noisier behavior in SeqLC, disclosure is almost complete at 95%, pointing to experimentation behavior that leads to equilibrium outcomes.

Result 5: *In the sequential treatments, the timing of the decisions follows the hypothetical decision sequence, in which high-productivity workers reveal before low-productivity workers. In the two simultaneous treatments, there is no clear pattern in the timing of choices.*

8. Conclusion

A well-established and influential theoretical literature shows that information revelation should be complete and immediate. Since "no news is bad news," senders are forced to reveal information. However, information unraveling is often incomplete in experiments. Not all senders disclose information, and sometimes even the senders with more favorable information conceal it.

Our paper explores limited depth of reasoning (Nagel, 1995; Stahl and Wilson, 1995; Bosch-Domenech et al., 2002) as a force that impedes information unraveling.[22] Level-k reasoning can be relevant because players with more favorable information typically have an incentive to reveal, while those with less favorable information must anticipate the behavior of others. This can lead to mistakes and a failure to reveal. Two design features reduce the requirements on subjects' depth of reasoning and the fragility of unraveling in the presence of non-strategic decisions. In the quasi-sequential treatments, subjects observe the current decision profile of the group and its payoff implications on the screen. Thus, decision-making is quasi-sequential and the decision to reveal information does not require more than one level of reasoning. The low-cost treatments guarantee that no single player (for example, a level $k = 0$ player) can stop the unraveling process by choosing to conceal. Our results show that when both treatment variants are implemented together, almost complete information revelation is achieved.

[21] The five-minute window was extended in 14 out of 44 groups: in one group in each Sim treatment, and in five and seven groups in SeqHC and SeqLC, respectively. Most of the clicks (about 80%) after the 300-second mark were made by six people, with one person alone accounting for 55% of them.

[22] Milgrom and Roberts (1986) already distinguish between sophisticated and unsophisticated players. Another model of bounded rationality suggesting limited information unraveling is cursedness (Eyster and Rabin (2005)). See Frondel et al. (2020) for an application of cursed equilibria to information revelation in the housing market.

The level-k model is useful for organizing the evidence. First, the minimum level of reasoning required at the treatment level correctly predicts the impact of our treatment variables: Sequential moves and low costs lead to more revelation. Second, we calibrate the outcomes of the revelation game using the distribution of k-levels elicited in a previous study and allowing for any level $k = 0$ behavior. This calibration allows us to predict not only ranges of average revelation rates for each treatment and the frequency of full revelation, but also the workers' productivity-specific revelation rates. We find that these calibrated predictions are consistent with observed behavior: For most predictions, we can find a level $k = 0$ behavior that rationalizes the data.

A final piece of evidence on the revelation process comes from the five-minute window during which subjects make their decisions in the quasi-sequential treatments. We find that the hypothetical dynamics of information unraveling are consistent with the actual sequence of decisions. Given a specific decision profile participants see on the screen, the players who have an incentive to reveal are those who most frequently reveal. We conclude that the level-k model is useful for capturing which players reveal, how often they reveal, and even when they reveal.

Declaration of competing interest

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Appendix A. Calibration

A.1. Level-k requirements

We start with an overview of the different minimum k requirements and a rough intuition for the impact of the p_0 assumption. A formal derivation is given below. Fig. 8 provides a summary of all possible level-k requirements in all treatments. There are two different distributions of minimum-k for SimHC, four for SimLC, and only one for both sequential treatments.

We would like to make two general remarks before we explain the actual changes between these distributions. First, higher levels of reasoning are irrelevant for the sequential treatments. Here, subjects do not face strategic uncertainty, and they cannot have incorrect beliefs. As a consequence, the canonical level-k model where level-k players expect all other players to reason at level $k - 1$ can strictly speaking not be applied to the sequential treatments. Here, the only question is whether or not a subject best-responds to the (pure) strategy profile shown on the screen. We argue that subjects who do not best-respond are essentially $k = 0$ players who pick an arbitrary action, that is, they reveal with probability p_0. Subjects in the sequential treatments will best-respond to the behavior of the other players if they are $k > 0$ players. Since the decision profiles shown on the screens only involve pure strategies, the requirements for optimal play in the sequential treatments are constantly $k \geq 1$ and do not depend on p_0.

Second, in the main text we have already explained how to derive the minimum k-levels for $p_0 = 0$ and $p_0 = 1$. These distributions are also shown in the figure (compare, the upper left panel for SimHC, and the lower left panel for SimLC), and the minimum k-levels for these extreme cases provide a lower and upper bound for the general minimum k-levels: If $p_0 = 0$ implies a minimum k-level of x for some worker, there is no $p_0 \in [0; 1]$ that implies a minimum k-level $x' < x$. If $p_0 = 1$, the individual minimum k levels are augmented by $+1$ in the Sim treatments, as explained in footnote 13. The minimum k-levels for $p_0 = 1$ represent an upper bound for the general minimum k-levels.

The figure documents that there are two distinct sets of minimum k-levels for SimHC, and four for SimLC. The two sets for SimHC are the ones for the extreme cases $p_0 = 0$ and $p_0 = 1$. There is one discontinuity at $p_0 = 0.495$. For lower values of p_0, W1's expected profits from concealing when reasoning at level-$k = 1$ are less than $\theta_1 - c = 507$, and for higher values they exceed the profits from revealing. In the former case, W1 reveals at $k \geq 1$ and in the latter case reveal at $k \geq 2$. Of course, this affects the behavior of the other workers as well. If W1 reveals at $k \geq 1$, W2 will reveal at $k \geq 2$, and so on. If W1 reveals at $k \geq 2$, W2 will only reveal at $k \geq 3$, and so on.

In SimLC, there are three critical values of p_0. The first discontinuity occurs at $p_0 = 0.825$ and affects W3 and W5. At this value, W3's expected profits from concealing at $k = 1$ start to exceed the corresponding profits from revelation such that W3 stops revealing at $k = 1$. At the same time, W5 will no longer reveal at $k = 2$. The reason for this is the changed behavior of W3. The second threshold, at $p_0 = 0.885$, foremost affects the behavior of W2 who will conceal at level $k = 1$ if $p_0 \geq 0.885$. The final threshold is near $p_0 = 0.915$. Here, W1's expected profits from concealing at $k = 1$ exceed the profits from revealing, so W1 no longer reveals at $k = 1$. This change also causes W4 to stop revealing at $k = 2$.

A.2. Formalization of the level-k requirements

In what follows, we provide a formal description of the procedure used to derive the minimum k-levels required for revelation for a given level $k = 0$ assumption. Let Ξ be the set of possible pure strategy profiles and let ξ^l be a typical element of Ξ. Since we have $n = 6$ players, there are 2^6 pure strategy profiles, so $|\Xi| = 64$. Let I_j^l denote worker Wj's action in profile l, that is, $\xi^l = (I_1^l, I_2^l, I_3^l, I_4^l, I_5^l, I_6^l)$. Let κ_0 denote the share of $k = 0$ players.

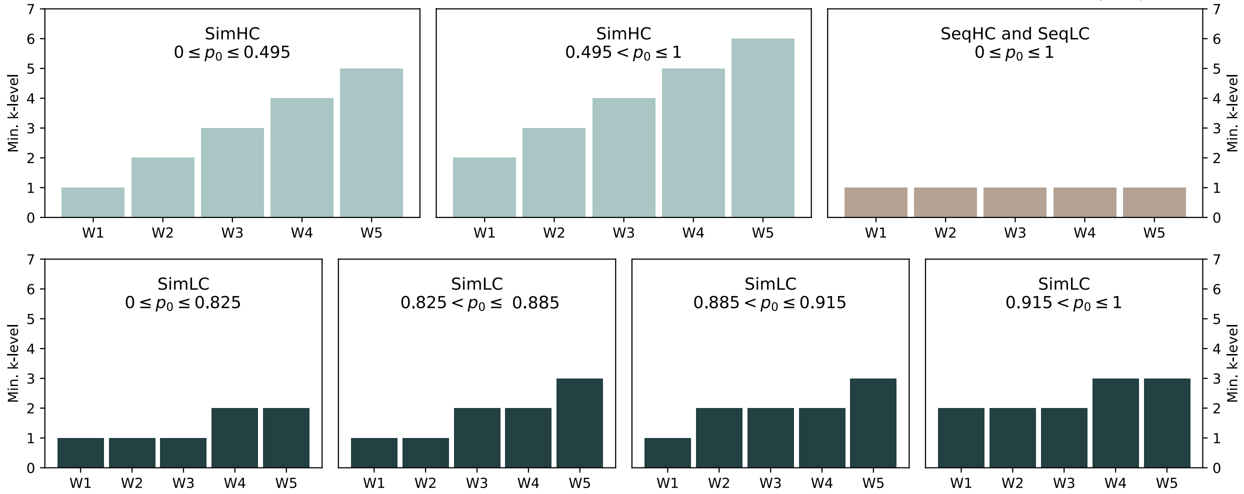

Fig. 8. Minimum k-levels requirements and their relation to the p_0 assumption for all treatments.

In general, we need to calculate when the profit from revealing, $\theta_i - c$, exceeds the one from concealing. The overall expected payoff from concealing is the sum of conceal payoffs in all profiles times the likelihood that each profile will occur from the perspective of worker Wi with level k_i:

$$\pi_i^{con}(k_i) = \sum_{\xi^l \in \Xi} Prob(k_i, \xi^l) \cdot \pi_i^l \qquad \text{with} \qquad \pi_i^l = \frac{\theta_i + \sum_{j \neq i}(1 - I_j^l)\theta_j}{1 + \sum_{j \neq i}(1 - I_j^l)}, \tag{2}$$

where π_i^l is the payoff from concealing, given the actions I_j^l, $j \neq i$ of workers Wj in profile ξ^l. A level-k player believes that the strategy profile (ξ^l) will be played with probability:

$$Prob(k_i, \xi^l) = \prod_{j=1}^{6} p_j(k_i - 1) \cdot I_j^l + (1 - p_j(k_i - 1)) \cdot (1 - I_j^l),$$

where $p_j(k-1)$ denotes the probability that player j will choose reveal when reasoning at level $k-1$. Player i with level k will typically believe there is one pure-strategy profile which occurs with probability one. The probabilities $p_i(k_i)$ are

$$p_i(k_i) = \begin{cases} p_0 & \text{if } k_i = 0 \\ \sigma_i & \text{otherwise} \end{cases} \qquad \text{with} \qquad \sigma_i = \begin{cases} 1 & \text{if } \theta_i - c > \pi_i^{con}(k_i) \\ \frac{1}{2} & \text{if } \theta_i - c = \pi_i^{con}(k_i) \\ 0 & \text{otherwise} \end{cases}$$

Note that the definition is recursive and that the probabilities will typically be either zero or one. Next, we can use the predictions for level-k players' behavior to derive the minimum k-level required for revelation. Technically, this is the lowest k_i for which worker Wi chooses to reveal with probability one.

A.3. Predicted probability of observing a given strategy profile

Having derived the individual minimum k requirements in the previous subsection, we can now turn to the actual predictions of calibration exercise. To do so, we first consider the predicted probability of observing some profile $\xi^l \in \Xi$ for some level $k = 0$ assumption $p_0 \in [0, 1]$.

In the sequential treatments, level $k = 0$ workers reveal with probability $p_0 \in [0, 1]$, and higher level players reveal whenever they have an incentive to do so; if indifferent, we assume they reveal with probability 0.5. The probability that the behavior of worker Wi is consistent with action I_i^l in profile ξ^l is

$$P_i^l = \begin{cases} \kappa_0 \cdot p_0 + (1 - \kappa_0) \cdot \sigma_i^l & \text{if } I_i^l = 1 \\ \kappa_0 \cdot (1 - p_0) + (1 - \kappa_0) \cdot (1 - \sigma_i^l) & \text{if } I_i^l = 0 \end{cases}$$

where

$$\sigma_i^l = \begin{cases} 1 & \text{if } \theta_i - c > \pi_i^l \\ \frac{1}{2} & \text{if } \theta_i - c = \pi_i^l \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

and where π_i^l is the same as in equation (2). In words, worker Wi reveals with probability p_0 with level $k = 0$, which is the case with probability κ_0, or if Wi is $k > 0$, which occurs with $1 - \kappa_0$, and provided $\theta_i - c > \pi_i^l$.

Revealing or concealing is consistent with action I_i^l in profile ξ^l with P_i^l. The overall probability that strategy profile ξ^l is observed is $P^l = \prod_{j=1}^{6} P_j^l$.

The approach for the simultaneous treatments is similar. Let s_i be the share of workers Wi satisfying the minimum k-level for revelation, then the probability that the worker's action is consistent with I_i^l in profile ξ^l reads

$$Q_i^l = \begin{cases} \kappa_0 \cdot p_0 + s_i & \text{if } I_i^l = 1 \\ \kappa_0 \cdot (1 - p_0) + (1 - \kappa_0 - s_i) & \text{if } I_i^l = 0 \end{cases}$$

The probability that strategy profile ξ^l is observed is then $Q^l = \prod_{j=1}^{6} Q_j^l$. To compute the different values of the s_i, we use an existing empirical distribution of k-levels (see Section 4.2).

A.4. Predicted revelation rates

Having calibrated the likelihood of all 64 pure-strategy profiles, we obtain as general predictions the workers' productivity-specific revelation rates and the aggregate revelation rate (our key variables). The predicted average revelation rate of worker Wi is obtained by summing over all outcomes and multiplying with the likelihood of that outcome:

$$\text{Sequential: } r_i = \sum_{l=1}^{64} P^l \cdot I_i^l \qquad \text{Simulatenous: } r_i = \sum_{l=1}^{64} Q^l \cdot I_i^l$$

The aggregate revelation rate of all workers expected to reveal in equilibrium (workers Wi, $i = 1 \ldots 5$) is:

$$r = \frac{1}{5} \sum_{j=1}^{5} r_j.$$

Appendix B. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.geb.2025.09.004.

Data availability

The data will be made available under https://heidata.uni-heidelberg.de/, a large open data depository.

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