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Information Unraveling and Limited Depth of Reasoning*

Volker Benndorf† Dorothea Kübler‡ Hans-Theo Normann§

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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.

JEL Classification numbers: C72, C90, C91

Keywords: information revelation, level-k reasoning, sequential decisions, calibration.

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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, 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, Kübler, and Normann, 2015; Benndorf, 2018; Hagenbach and Perez-Richet, 2018; Penczynski and Zhang, 2018; Jin, Luca, and Martin, 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 unrav-

[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.

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

eling experiments (see Benndorf, Kübler, and Normann, 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, Kübler, and Normann (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

[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, Kübler, and Normann, 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.

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 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 dis-

[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.

closure 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 analyses 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

[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, Frank, and Maksimovic (1990), Cadsby, Frank, and Maksimovic (1998), Brandts and Holt (1992), Brandts and Holt (1993), Cooper, Garvin, and Kagel (1997a), Cooper, Garvin, and Kagel (1997b), Potters and Van Winden (1996), Cooper and Kagel (2003), Kübler, Müller, and Normann (2008), Jeitschko and Normann (2012), and 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, Lai, and Lim (2020), some players have private information that is relevant to the decisions made by others. Experimental analyses include Dickhaut, McCabe, and Mukherji (1995), Forsythe, Lundholm, and Rietz (1999), Blume et al. (1998), and Blume et al. (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 and Walker, 1988; Bochet, Page, and Putterman, 2006; Andersson and Wengström, 2007; Bochet and Putterman, 2009; Fonseca and Normann, 2012; Oprea, Charness, and Friedman, 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.

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, Isaac, and Palfrey (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, Lundholm, and Rietz (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, Kübler, and Normann, 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, Kübler, and Normann (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, Luca, and Martin (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.

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, Li, and Tolksdorf (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, Gerster, and Vance (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

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

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, Kübler, and Normann (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).

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

Table 1: 2×2 treatment design.

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 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

[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 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.

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 Material 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, Kübler, and Normann (2015) for a proof. Which players reveal or conceal in equilibrium depends on the set of productivities $\Theta = \{\theta_1, \theta_2, \ldots, \theta_n\}$ and the cost of revelation c. The worker with the lowest productivity has a strictly dominant strategy to conceal as long as $c > 0$.

[10] In the field, people may not observe the full decision vector of others 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 **agranov2015cp** 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.

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:

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

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

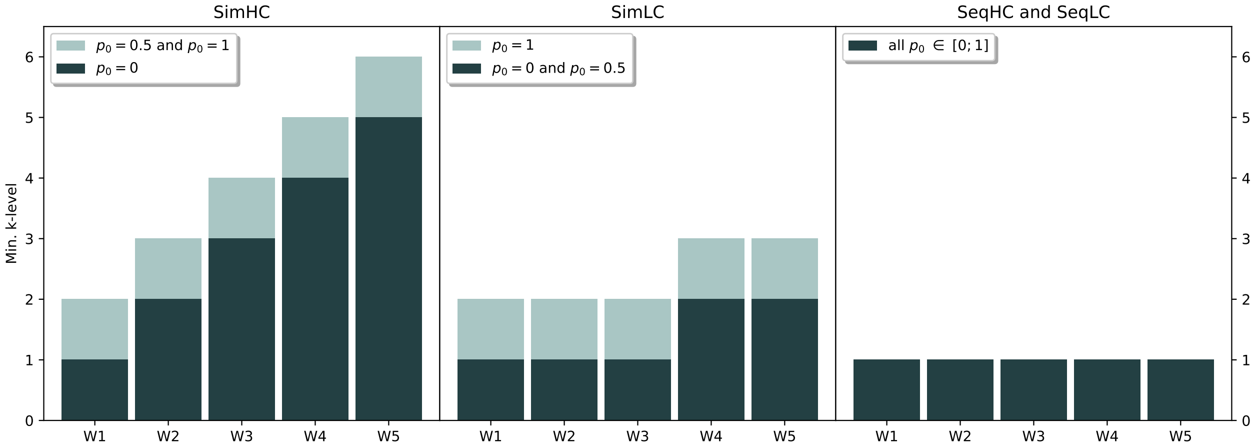

Figure 1: Minimum level-k requirement for workers W1 to W5.

$k = 2$ 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 $\theta_i \leq 551$). Worker W1 with level $k = 2$ would reveal as before. And so on: Our parameters in SimHC are chosen such that a worker Wi, $i \leq 5$, reveals if and only if the level of reasoning is $k \geq i$.

Figure 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 $\theta_i, i \leq 5$, reveal if and only 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 Figure 1, we have that $\theta_i - 28 \geq 483$, 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 $k \geq 2$.

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. Figure 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 Figure 1. Figure 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 Figure 1. In SeqHC, worker W1 reveals as long as the level of reasoning is $k \geq 1$, 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, $i \leq 5$, $k = 1$ is sufficient to reveal.[14] The 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

[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 Figure 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 $k \geq 1$ is required for disclosure because $k = 0$ level players may conceal, as their choice is non-strategic.

workers disclose (see Figure 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 $r_{HC}^t < r_{LC}^t$, $t \in \{Sim, Seq\}$.

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 is highest 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.

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

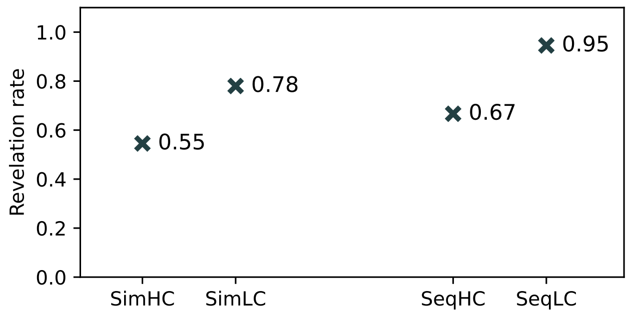

Figure 2: Average revelation rates by treatment, using data from workers W1 to W5.

Our main result is shown in Figure 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, Kübler, and Normann (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 $\times$ 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 $\times$ 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

[16]We exclude worker W6 from the calculation of the aggregate (treatment-level) disclosure rates as well as from the regression analyses 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.

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.

pairwise comparisons within the 2×2 design, we find significant differences between $r_{HC}^{Sim} < r_{LC}^{Sim}$ (Mann-Whitney U, $p = 0.024$) and $r_{LC}^{Sim} < r_{LC}^{Seq}$ ($p = 0.030$). The comparison of r_{HC}^{Seq} and r_{LC}^{Seq} 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

Figure 3 shows that the workers' productivity-specific revelation rates 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

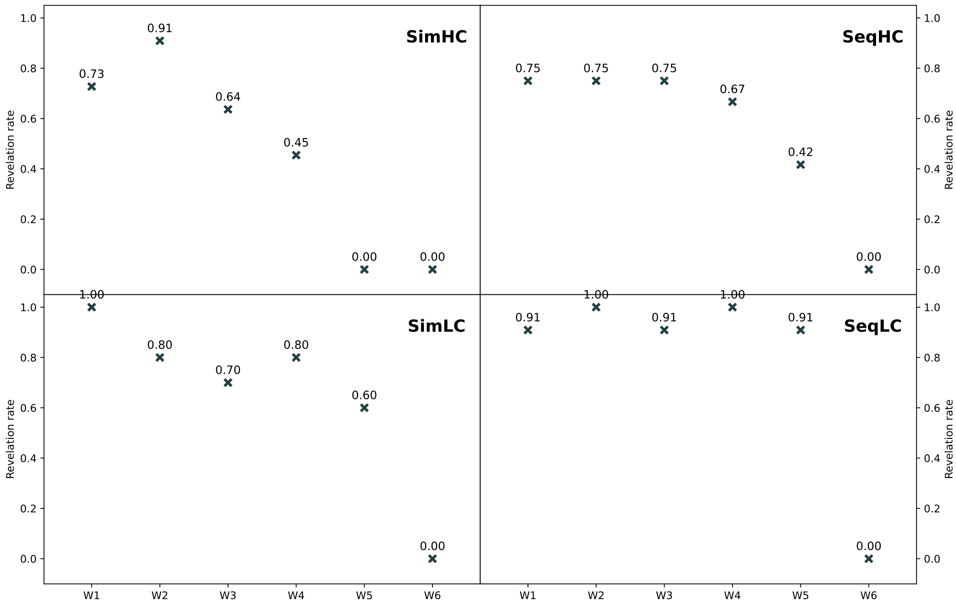

Figure 3: Workers' productivity-specific revelation rates by treatment, using data from all workers.

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.*

We can relate the finding of a negative correlation of disclosure behavior with productivity to the minimum k-levels for each worker Wi in Figure 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 much 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, Kübler, and Normann (2017) who used a variation of the SimHC treatment to elicit subjects' k-levels.[17] Figure 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.

[17]The participants in Benndorf, Kübler, and Normann (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.

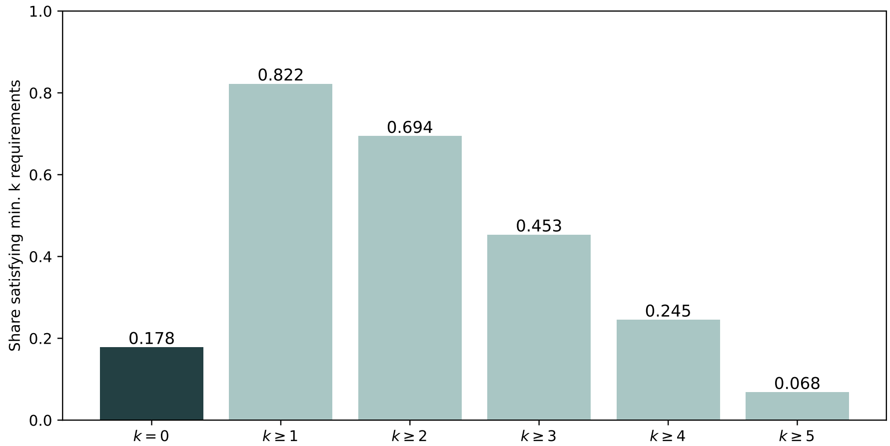

Figure 4: Share of level $k = 0$ players and share of players who meet a given minimum k requirement, based on data from Benndorf, Kübler, and Normann (2017).

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 Figure 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

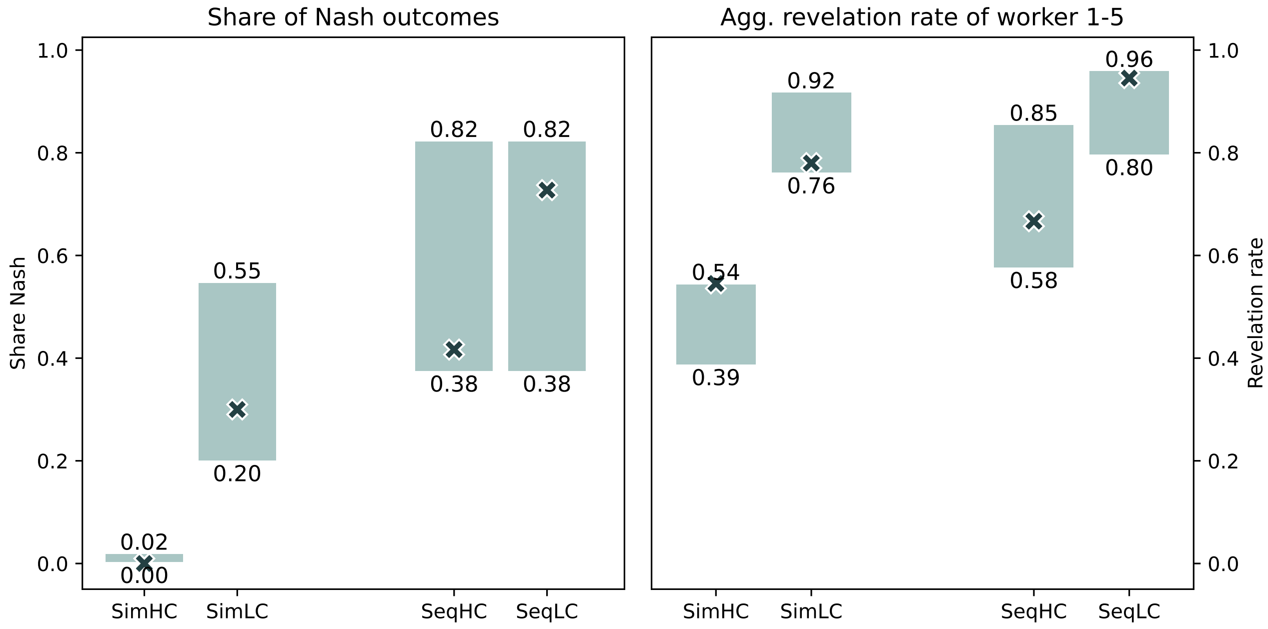

Figure 5: Calibrated and observed frequency of the Nash equilibrium outcome, by treatment (left panel); calibrated and observed aggregate revelation rates of workers W1 to W5, by treatment (right panel).

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 Figure 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 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 Figure 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 Figure 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 Figure 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 Figure 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 Figure 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 Figure 6. Taking the 24 calibrated intervals

[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, Kübler, and Normann (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.

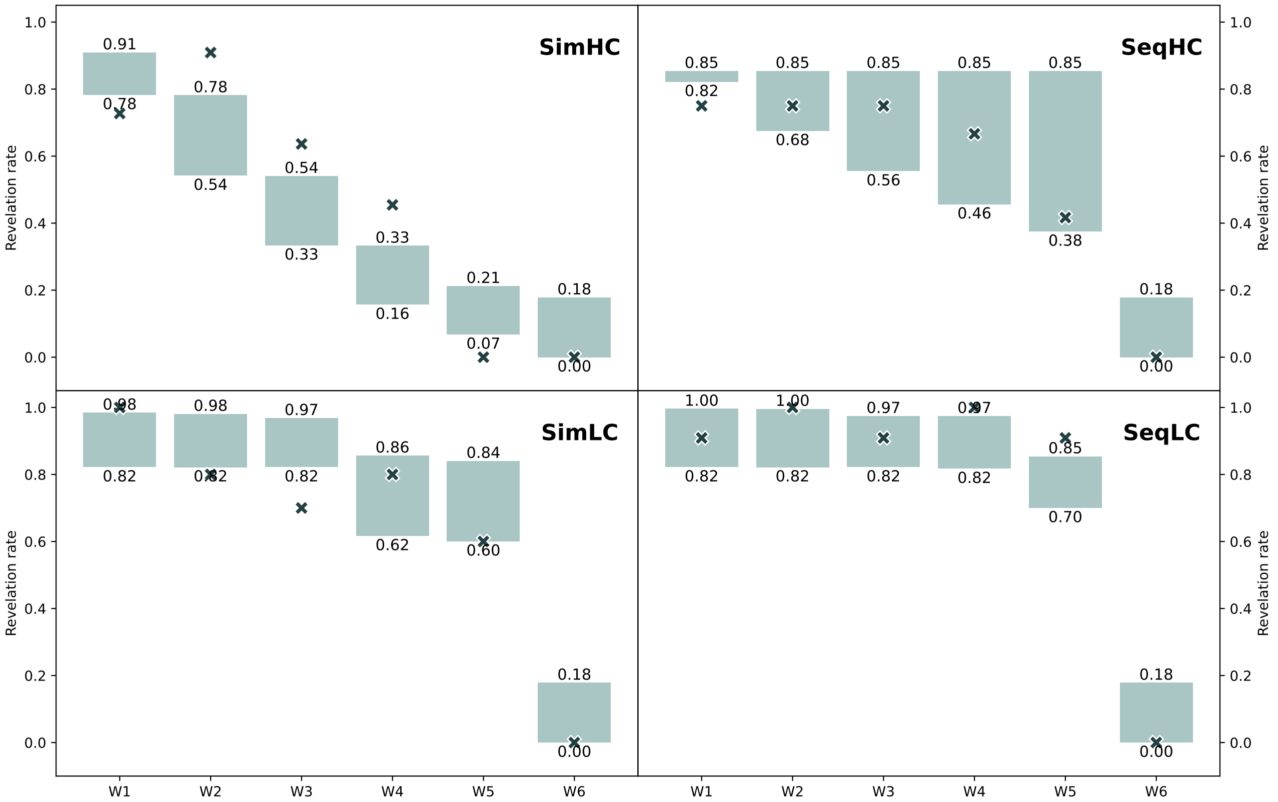

Figure 6: Calibration results (boxes) and data (crosses), workers' productivity-specific revelation rates by treatment, using data from workers W1 to W6.

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 $p < 0.001$.

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

$$Observation_i = \beta_0 + \beta_1 \cdot Prediction_i + \epsilon_i.$$

We include all data points reported in Figures 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.*

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.

Figure 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 Figure 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

[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 $p > 0.313$).

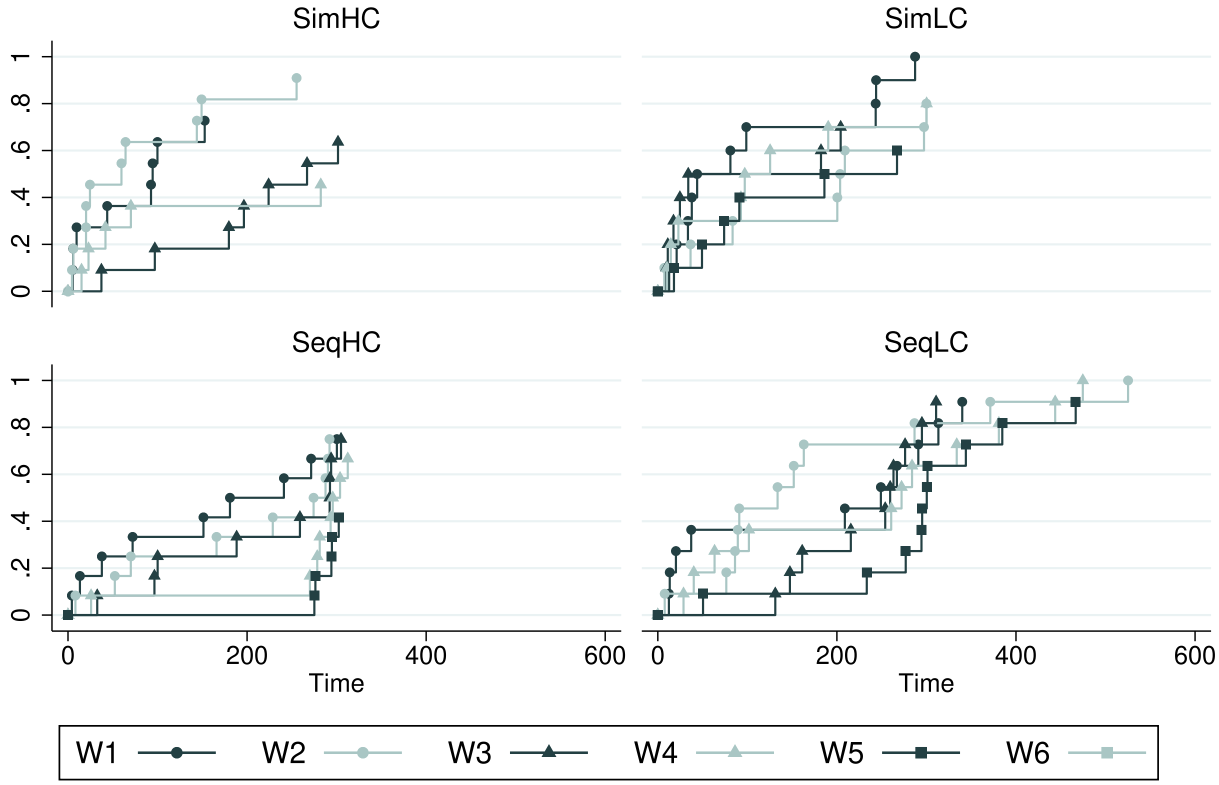

Figure 7: The percentage of workers who have made their final decision to reveal at a given point in time (in seconds).

revelation rates reported in Figure 3.

Figure 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, $j = 2, ..., 5$ 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 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).

SeqHC

Profile	On screen time	On screen count	Which worker reacts 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

Profile	On screen time	On screen count	Which worker reacts 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

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.

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 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 Figure 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

[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. An-

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.

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.

other model of bounded rationality suggesting limited information unraveling is cursedness (Eyster and Rabin, 2005). See Frondel, Gerster, and Vance (2020) for an application of cursed equilibria to information revelation in the housing market.

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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. Figure 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 is constantly $k \geq 1$ and does 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 reveals 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.

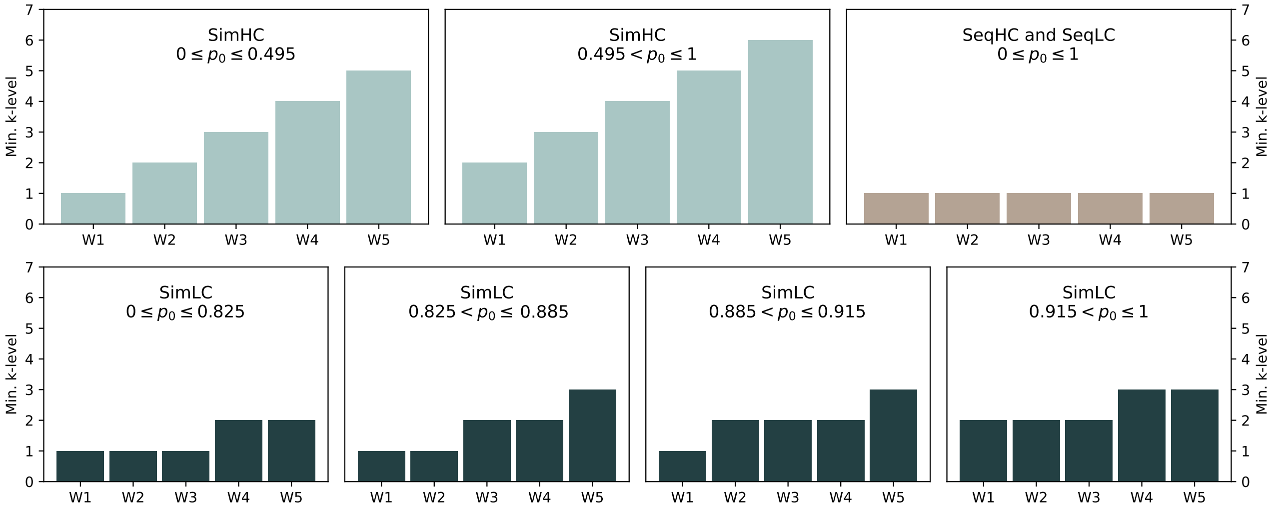


Figure 8: Minimum k-levels requirements and their relation to the p_0 assumption for all treatments.

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.

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, $i = 1...5$) is:

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

Supplementary Material

1 Additional treatments

We ran two additional treatments to investigate the reasons for the incomplete unraveling found in treatment SimHC, the baseline treatment in the original version of the paper. While a detailed documentation of the treatments and their results can be found in the previous version of this paper (see https://rationality-and-competition.de/wp-content/uploads/2023/01/354.pdf), we would like to briefly summarize the motivation and findings here. Our hypothesis was that social preferences can hinder full unraveling. The two treatments were conducted in the high-cost environment and are labeled *Entitlement* and *Unaware*.

In *Entitlement*, participants' productivities in the revelation game are tied to their performance in the real-effort task that was part of the experiment. The worker with the highest productivity is the subject who encoded the most words in the real-effort task, the worker with the second-highest productivity is the subject who encoded the second-most words, and so on. In the baseline treatment (SimHC), the role assignment is determined by a random computer draw. The idea behind the treatment manipulation in *Entitlement* is that linking the role assignment to real-effort performance may mitigate other-regarding motives such as inequality aversion or joint-surplus maximization. Participants may feel more inclined to maximize their own profits because they performed better, even though this imposes a negative externality on other players in their group.

The *Unaware* treatment is designed to reduce subjects' awareness of the negative externalities they impose on others when they reveal. Subjects are not informed about the negative externalities of revealing. In particular, the instructions do not explain the profit function when concealing but only know that their profit depends on others' choices. Subjects only learn that their concealment profits depend on the behavior of the other workers in their group. Furthermore, the decision screen does not display any information about the other members of the group or their behavior. However, it does display the subject's two potential profits given the current strategy profile of the group, so subjects can still learn the payoff function. Thus, subjects are still able to identify optimal behavior even though the exact payoff function is ex-ante unknown.

We expected that both treatments would reduce the role of social preferences and thus increase unraveling. However, the results do not support this hypothesis. While revelation rates are higher in Entitlement and Unaware than in Sequential, these differences are not significant.

2 Instructions

(Translated from the German original. Parts in italics differ across treatments.)

Instructions for the first part

In the following experiment, you have the opportunity to earn money, depending on your behavior.

Please turn off your mobile phone now and do not talk to the other participants. Adherence to these rules is very important. If you have any questions while reading these instructions or during the experiment, please raise your hand. We will then come to you immediately and answer your question individually.

Today's experiment is divided into two parts. The two parts are independent of each other. Your decisions in the first part have no influence on the second part and vice versa.

Part 1 is about an effort task. It is described below.

Exactly how much you earn will be decided in Part 2. You will receive separate instructions for part 2 after the first one has been completed. But we can already say this much here:

- Everyone receives a starting amount of 2 €. In addition, the following applies:
- You will be divided into (randomly assembled) groups of 6.
- In the second part, the participants will have different levels of productivity.
- These productivities are randomly assigned. Your performance in the first part of the experiment does not affect your potential earnings in the second part.
- The higher the productivity, the higher the payout you can guarantee yourself by your decision. The guaranteed payouts you can secure for yourself in Part 2 are:

Highest productivity	*2.00 € + 10.14 €*
2^{nd} *highest productivity*	*2.00 € + 9.64 €*
3^{rd} *highest productivity*	*2.00 € + 9.02 €*
4^{th} *highest productivity*	*2.00 € + 8.20 €*
5^{th} *highest productivity*	*2.00 € + 6.96 €*
Lowest productivity	*2.00 € + 4.00 €*

Table for high cost

Highest productivity	*2.00 € + 11.58 €*
2^{nd} *highest productivity*	*2.00 € + 11.08 €*
3^{rd} *highest productivity*	*2.00 € + 10.46 €*
4^{th} *highest productivity*	*2.00 € + 9.64 €*
5^{th} *highest productivity*	*2.00 € + 8.40 €*
Lowest productivity	*2.00 € + 4.00 €*

Table for low cost

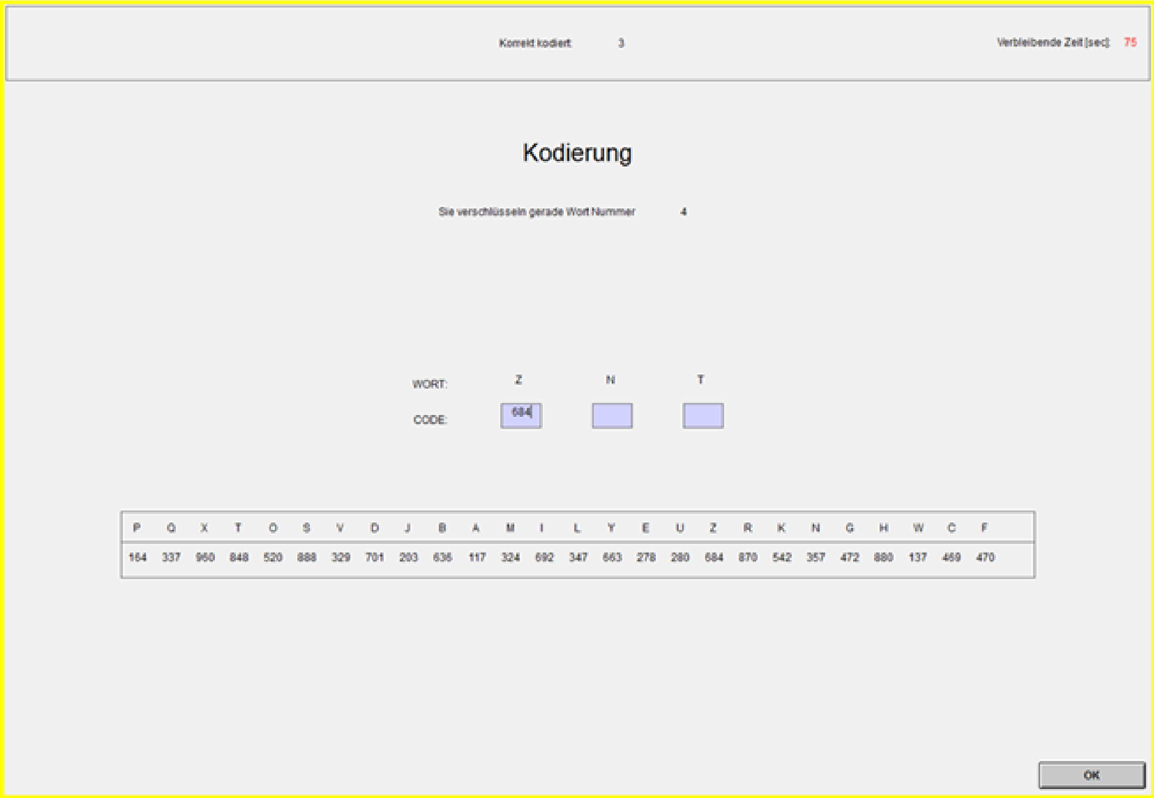
Which payout you will actually receive is decided in part 2, which will be explained in detail later. Depending on the decisions, there may be deviations from the guaranteed payouts mentioned.

General structure of Part 1

In the first part of the experiment there are two different phases, the practice phase which is intended to familiarize you as much as possible with the effort task before the actual experiment begins, and the actual work phase.

- Practice Phase:
  In the practice phase, all participants have to correctly complete 10 words. Please note that correct solutions in the practice phase do not lead to payouts.

- Work phase:
  The working phase lasts 10 minutes. Your task is to correctly encode as many words as possible in this time. As mentioned above, performance in the work phase will *Sim, Seq, Unaware: not* affect your earning potential in the second part.



The effort task

During the experiment, you will have the opportunity to complete an effort task. The effort task consists of encoding letter combinations (words) into numbers. Three capital letters always correspond to one word. Each capital letter must be assigned a number. The coding for this can be found in the table below. Please have a look at the screenshot:

In this example, the participant has already correctly coded 3 words (see field: above). Now the 3 capital letters: "Z", "N" and "T" must be coded here. The solution follows from the table:

- For "Z" you need: 684 (see current entry of the participant)
- For "N" you need: 357
- For "T" you need: 848

To enter, please click on the blue box below the first capital letter. Furthermore, the computer screen (see screenshot on page 1) displays the following information:

- "Correctly encoded" = Number of words already encoded correctly.
- "Remaining time [sec]" = Remaining time in the current period.
- "You are currently encrypting word number" = Current word number.

When all 3 numbers have been entered, please click on the "OK" button with the mouse.

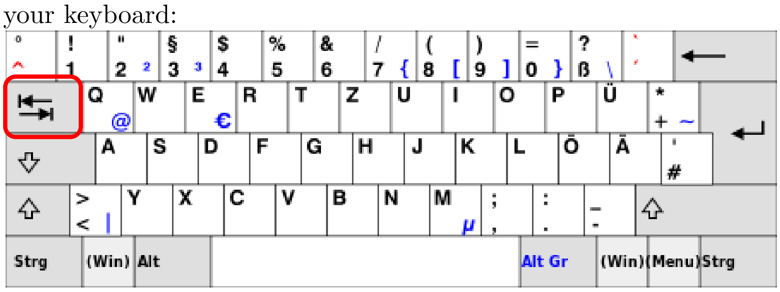
- The computer then checks whether all capital letters have been correctly encoded in numbers, that is, whether all 3 numbers have been entered correctly according to the table. Only then is the word evaluated as correct. After that, a new word (consisting of 3 capital letters) is randomly drawn.

- Furthermore, the table is randomly reshuffled in two steps:
  - New three-digit numbers are randomly selected and entered into the table as new assignments for the capital letters.
  - Furthermore, the position of the capital letters is randomly rearranged in the table. Please note that all 26 capital letters of the Latin alphabet are always used for this.

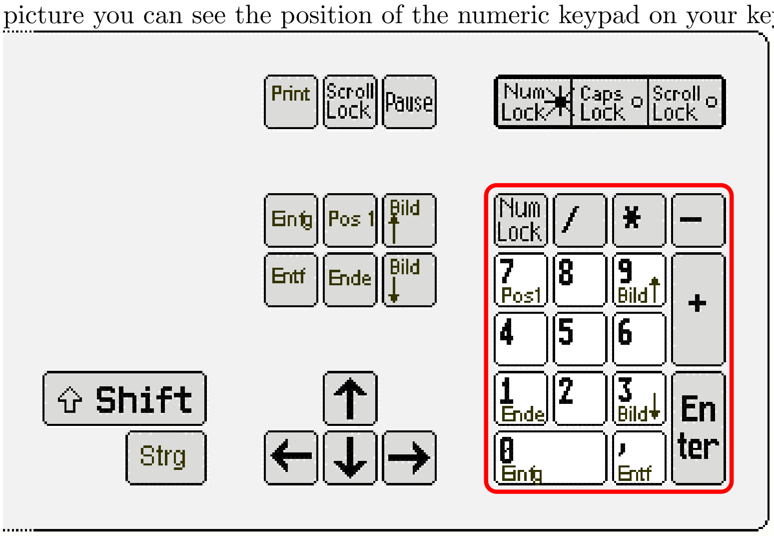
  Please note, if a new word appears, you must click with the mouse on the first of the three blue boxes. Only then are new entries possible!
- If an incorrect entry is made, the computer will indicate this (in red text) after the “OK” button has been pushed.
- Please consider:
  - The current word remains to be solved until a correct entry is made.
  - However, your previous entries (in the 3 fields below the capital letters) will all be deleted.
  - Furthermore, the table remains unchanged, that is, the assigned numbers remain identical. Likewise, the position of the capital letters in the table does not change.

Notes

- Please note that after entering the three-digit number combination, you can easily switch to the next blue field by pressing the TAB key on your keyboard.emain identical. Likewise, the position of the capital letters in the table does not change. In the following picture you can see the position of the tab key on your keyboard:



- It is faster to enter numbers using the numeric keypad (on the right) on the keyboard . In the following picture you can see the position of the numeric keypad on your keyboard:



Instructions for the second part

In this part of the experiment, all participants take on the role of different workers. For this purpose, the participants are sorted into different markets. Each market consists of six participants or workers. As already mentioned in part 1, this sorting is purely random.

The workers in this experiment differ in terms of their productivity. Each worker in a market has a different productivity. The productivity of a worker determines the earnings of a fictitious employer (played by the computer) and thus also the wage that the worker can receive from the fictitious employer. The exact values can be found in the following table.

Worker 1	607
Worker 2	582
Worker 3	551
Worker 4	510
Worker 5	448
Worker 6	200

The assignment of the different productivities is also purely random, that is, a random computer draw will decide which participant gets a higher or lower productivity.

Now for your task:

Every worker makes the following decision: You choose whether or not to reveal your productivity. Revealing costs a fee of *high cost: 100 points / low cost: 28 points* (imagine having a certificate created, which is then presented to the fictitious employer). Your payoff depends on this decision as follows:

If you have chosen to reveal your productivity, you will receive as a reward your productivity in points minus the fee of *high cost: 100 points / low cost: 28 points.*

If you do not reveal your productivity, you get as a reward the average productivity of all participants (in your market) who did not reveal their productivity.

At the beginning, as long as no worker has revealed his productivity, the average productivity of all workers who do not reveal is:

$$\frac{607 + 582 + 551 + 510 + 448 + 200}{6} = \frac{2898}{6} = 483$$

So in this case all participants would receive 483 points. For example, if workers 4 and 2 reveal their productivity, the average changes to 451.50. So in this case, workers 1, 3, 5, and 6 would receive 451.50 points and workers 4 and 2 would receive *high cost: 410 and 482 points / low cost: 482 and 554 points*, respectively.

All workers in a market decide at the same time whether or not they themselves want to reveal their productivity. At this stage of the decision, there are several things to consider:

- At the beginning of the decision phase, a timer of 300 seconds starts.
  - This timer is displayed in the lower right area of the screen.
  - It is the same for all workers in a market.
  - The decision phase ends when the timer reaches 0.
- As long as the timer has not expired, each participant can change their decision (even multiple times). *Sim: Only the decisions selected at the end of the round are relevant for your payment.*

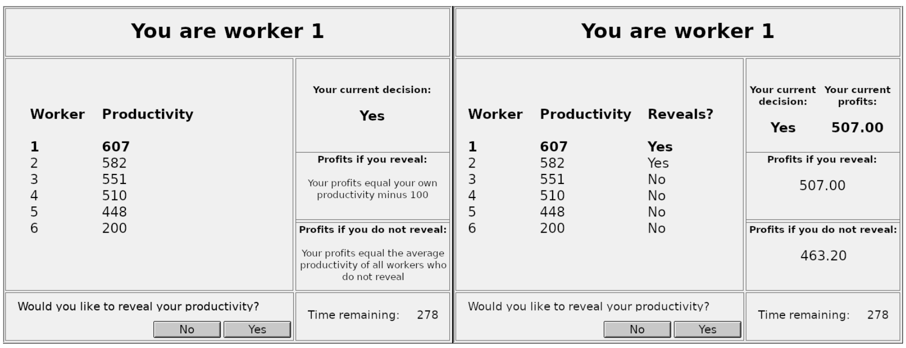
Seq:

- *If a participant changes his decision and less than 10 seconds remain on the timer, 10 seconds will be added to the timer. So the decision phase ends only when all participants have not changed their decisions for more than 10 seconds. So it is not possible to catch the other participants off guard by making last second changes.*
- *If a participant changes his decision, the other participants are informed about this change. All participants know the decisions of all participants at any time. This also includes information about their own current earning potential.*

- *Sim:*
  The screenshot on the last page (left panel) shows the decision phase from the point of view of worker 1. At the top you can see which worker you are. The large field on the left indicates the productivity of the different workers in your market. To the right is your own current decision. Below that, you can see again how to calculate your profit if you do or do not reveal your productivity. Your "profit if you reveal" is always equal to your own productivity minus the fee of high cost: 100 points / low cost: 28 points. The "profit if you do not reveal" depends on the decisions of the other participants in your market. It is equal to the average productivity of the participants in your market who do not reveal. The timer is displayed in the lower right corner. To the left of it, you can change your decision by clicking on the corresponding button.

- *Seq:*
  The screenshot on the last page (center panel) shows the decision phase from the point of view of worker 1. At the top you can see which worker you are. The large box on the left indicates which workers are currently revealing or not revealing their productivity. To the right, your own current decision and your own current profit are displayed. Below you can see how much you would earn if the other workers stick to their current decision and you reveal or do not reveal your productivity. Your "profit if you reveal" is constant and never changes. The "profit if you do not reveal" changes whenever one of the other participants changes his decision (but not if you yourself change your decision). The timer is displayed in the lower right corner. To the left of it, you can change your decision by clicking on the corresponding button.

At the end of the experiment, your earnings will be converted to Euros at an exchange rate of 50 points = 1 Euro and rounded up to the next higher 50 cent amount. Please also note that there are no repetitions in this experiment. There is only one round.



Reproduction of the decision screens. The left panel is for SimHC, the right panel for SeqHC.

3 Additional tables

	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	0.00	0.06	0.04	0.04
000001	1.5	1.0	0.00	0.00	0.00	0.00	0.00	1.00	0.00
000010	45.6	1.6	0.20	0.00	0.00	0.00	0.80	0.00	0.00
001000	49.4	3.3	0.56	0.06	0.23	0.00	0.15	0.00	0.00
001010	5.1	2.5	0.67	0.00	0.00	0.00	0.33	0.00	0.00
010000	13.4	1.8	0.19	0.52	0.17	0.00	0.13	0.00	0.00
010010	10.3	1.0	0.00	0.67	0.00	0.00	0.33	0.00	0.00
011000	8.7	1.8	0.45	0.20	0.25	0.00	0.10	0.00	0.00
011010	2.3	3.0	0.00	0.00	0.00	0.00	1.00	0.00	0.00
011100	21.1	1.0	0.00	0.00	0.00	1.00	0.00	0.00	0.00
011110	2.0	1.0	1.00	0.00	0.00	0.00	0.00	0.00	0.00
100000	25.9	2.7	0.20	0.53	0.08	0.07	0.12	0.00	0.00
100010	7.3	2.5	0.06	0.21	0.00	0.00	0.73	0.00	0.00
100100	17.4	2.0	0.00	0.00	0.67	0.17	0.17	0.00	0.00
100110	5.3	1.0	0.00	0.00	0.00	0.00	1.00	0.00	0.00
101000	30.9	3.0	0.07	0.17	0.46	0.14	0.16	0.00	0.00
101010	10.0	2.7	0.22	0.08	0.33	0.00	0.36	0.00	0.00
101100	8.9	1.6	0.00	0.37	0.07	0.57	0.00	0.00	0.00
101110	5.9	1.0	0.00	0.50	0.00	0.00	0.50	0.00	0.00
110000	34.6	2.7	0.19	0.03	0.61	0.05	0.13	0.00	0.00
110010	15.8	3.3	0.07	0.23	0.33	0.08	0.28	0.00	0.00
110100	12.1	1.7	0.00	0.00	1.00	0.00	0.00	0.00	0.00
110110	1.5	1.0	0.00	0.00	1.00	0.00	0.00	0.00	0.00
111000	30.1	2.9	0.03	0.02	0.25	0.55	0.12	0.00	0.03
111010	8.1	2.1	0.02	0.07	0.09	0.29	0.53	0.00	0.00
111100	51.6	3.6	0.04	0.05	0.05	0.11	0.53	0.06	0.17
111101	2.8	1.0	0.00	0.00	0.00	0.00	0.00	1.00	0.00
111110	84.1	4.4	0.03	0.06	0.04	0.28	0.35	0.10	0.15
111111	7.2	6.0	0.00	0.00	0.00	0.00	0.00	1.00	0.00

Table 1: All strategy profiles reached during the decision-finding phase in the SeqHC treatment.

	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
000001	56.9	5.0	0.60	0.40	0.00	0.00	0.00	0.00	0.00
000010	14.4	1.0	0.00	0.00	1.00	0.00	0.00	0.00	0.00
000100	0.7	1.0	0.00	0.00	0.00	1.00	0.00	0.00	0.00
001000	16.3	2.4	0.15	0.62	0.07	0.17	0.00	0.00	0.00
001001	2.3	1.0	0.50	0.50	0.00	0.00	0.00	0.00	0.00
001010	3.9	1.0	1.00	0.00	0.00	0.00	0.00	0.00	0.00
001100	4.1	1.0	0.00	0.50	0.00	0.50	0.00	0.00	0.00
010000	22.4	3.3	0.19	0.10	0.53	0.16	0.02	0.00	0.00
010001	43.7	13.3	0.64	0.33	0.00	0.01	0.00	0.02	0.00
010010	2.0	1.0	0.00	0.00	0.00	0.00	1.00	0.00	0.00
010011	7.5	1.0	1.00	0.00	0.00	0.00	0.00	0.00	0.00
010100	71.3	2.0	0.33	0.08	0.42	0.08	0.08	0.00	0.00
010101	6.5	6.0	0.50	0.00	0.00	0.50	0.00	0.00	0.00
010110	2.7	1.0	0.00	0.00	0.00	0.00	1.00	0.00	0.00
011000	33.4	7.3	0.40	0.08	0.04	0.29	0.03	0.15	0.00
011001	76.2	4.0	0.50	0.10	0.10	0.10	0.00	0.20	0.00
011010	2.1	1.7	0.33	0.00	0.00	0.17	0.17	0.33	0.00
011011	3.0	1.0	0.00	0.00	0.33	0.00	0.67	0.00	0.00
011100	11.7	3.6	0.48	0.00	0.10	0.15	0.24	0.03	0.00
011101	6.9	4.0	0.33	0.00	0.08	0.08	0.29	0.21	0.00
011110	14.9	4.0	0.54	0.00	0.00	0.05	0.21	0.17	0.03
011111	6.2	5.3	0.06	0.00	0.00	0.10	0.47	0.38	0.00
100000	5.0	2.0	0.35	0.12	0.33	0.20	0.00	0.00	0.00
100001	60.9	4.0	0.14	0.64	0.21	0.00	0.00	0.00	0.00
100100	9.3	9.0	0.00	0.03	0.32	0.00	0.65	0.00	0.00
100110	3.4	2.5	0.00	0.50	0.36	0.00	0.14	0.00	0.00
101000	20.0	3.4	0.27	0.21	0.25	0.22	0.00	0.05	0.00
101001	66.0	5.5	0.05	0.05	0.10	0.00	0.00	0.80	0.00
101010	3.4	1.0	0.00	0.50	0.00	0.00	0.50	0.00	0.00
101100	51.1	14.3	0.00	0.53	0.17	0.00	0.13	0.18	0.00
101101	10.2	5.0	0.00	0.06	0.00	0.28	0.00	0.67	0.00
101110	8.8	5.3	0.00	0.22	0.22	0.33	0.23	0.00	0.00
110000	22.9	2.8	0.38	0.25	0.13	0.25	0.00	0.00	0.00
110001	17.5	11.0	0.33	0.33	0.05	0.06	0.15	0.08	0.00
110011	7.0	4.0	0.00	0.00	0.00	0.00	1.00	0.00	0.00
110100	50.1	6.0	0.00	0.00	0.83	0.00	0.17	0.00	0.00
110101	2.2	2.5	0.50	0.00	0.50	0.00	0.00	0.00	0.00
110110	32.3	2.0	0.00	0.17	0.61	0.00	0.11	0.00	0.11
111000	15.9	5.0	0.24	0.26	0.06	0.19	0.25	0.01	0.00
111001	5.1	2.3	0.00	0.25	0.33	0.00	0.17	0.25	0.00
111010	12.6	2.2	0.13	0.00	0.00	0.53	0.33	0.00	0.00
111011	2.8	3.0	0.00	0.00	0.00	0.13	0.50	0.38	0.00
111100	35.7	16.1	0.04	0.11	0.15	0.05	0.61	0.04	0.01
111101	28.8	12.5	0.02	0.06	0.00	0.00	0.23	0.69	0.00
111110	70.3	14.1	0.06	0.04	0.04	0.05	0.31	0.21	0.28
111111	18.5	14.0	0.31	0.00	0.00	0.07	0.20	0.41	0.00

Table 2: All strategy profiles reached during the decision-finding phase in the SeqLC treatment.

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