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Preface

This dissertation was created during the time I was employed at the *Düsseldorf Institute for Competition Economics (DICE)* at the *Heinrich-Heine Universität Düsseldorf*. The research presented here has benefited from discussions with professors and students at DICE. I am very grateful to all who supported my research at DICE.

Parts of this thesis have been presented at international conferences and research seminars. I would like to thank the participants for helpful hints and comments.

In particular, I would like to thank my supervisor Hans-Theo Normann whose advice was crucial for this thesis. I am also thankful to my second supervisor Christian Wey and to my coauthor Dorothea Kübler. Moreover, I would like to thank Irina Baye, Georg Clemens, David Danz, Markus Dertwinkel-Kalt, Holger Rau and Tobias Wenzel, who all helped to improve this dissertation at various stages of its development.

Contents

Chapter 1

Introduction

The treatment of personal data is one of the key challenges at the beginning of the Information Age. An increasing amount of sensitive personal data is stored digitally and kept in databases for future analyses. Today, for example social networks store and analyze the information subjects share with their peers, online vendors keep detailed profiles of their customers, and smartphones may be used to track their owners' movements geographically. In the near future, such data collections are likely to contain more—and more sensitive—information. For instance, a recent patent of Apple's describes the use of ear buds to monitor "user characteristics [...] such as temperature, perspiration and heart rate".[1] Such innovation is giving rise to concerns that in days to come, even health-related data will be under close scrutiny.

The aim of this thesis is to analyze the economic aspects of privacy topics. This includes two different perspectives. On the one hand, we study whether and to what degree subjects have an economic valuation for their personal data. This aspect is dealt with in the second chapter. On the other hand, we also consider the question if economic decision making will have an adverse effect on privacy. This phenomenon is referred to as "unraveling of privacy" and it is addressed in the chapters three and four. Chapter 5 is also related to this field. Here, we consider iterative reasoning—a central prerequisite for unraveling to take place.

Chapter 2 is titled *"The Willingness to Sell Personal Data"*. The research is joint work with Hans-Theo Normann. It describes a laboratory experiment used to elicit subjects' valuation for keeping their personal data private. In the course of the experiment, lab participants are asked to sell personal information such as contact details and/or preference data to a large German company. This research is novel in that (i) the experiments are incentivized, (ii) the focus on privacy issues is salient, and (iii) the use of the data—marketing purposes—is transparent and unambiguous. There are two main insights from these experiments. The first result is that a large majority of the participants accept monetary offers in exchange for their personal data. Roughly five in six participants sell for

[1] Prest and Hoellwarth (2014).

example their contact information at prices as low as €5. However, there is also a minority of about one in six participants who persistently refuse to disclose their data. These subjects appear to be highly concerned about their privacy. They do not fall for rather incidental requests, and in another treatment, they waive up to €50 for their data.

The third chapter, *"Privacy Concerns, Voluntary Disclosure of Information, and Unraveling: An Experiment"*, is joint work with Dorothea Kübler and with Hans-Theo Normann.[2] Here, we consider a labor-market experiment where workers may reveal their productivity at a cost. Theoretically, such voluntary disclosure of information should result in unraveling of privacy. That means that a subject's private information may be unveiled even though the subject herself does not provide any details. The intuition is as follows: Workers with a high productivity have an incentive to disclose their type. Such rational revelation improves the worker's payoff, but it also reduces the expected productivity and therefore the wages of workers who do not provide any information. If the cost of revelation is negligible, all types except for the one with the lowest productivity will disclose their information in equilibrium. The type with the lowest productivity is then identified by the fact that she is the only one who does not disclose her type. Our experiment documents that such unraveling can be observed frequently although somewhat less than predicted. Equilibrium play is more likely when subjects are predicted to conceal their productivity than when they should reveal. This effect is primarily driven by workers of low productivity who sometimes manage to pool even though they should not be able to do so in equilibrium. This tendency of under-revelation is consistent with the level-k model (Nagel, 1995). We also find that a loaded frame where the private information concerns the workers' health status leads to less revelation.

The title of the fourth chapter is *"Voluntary Disclosure of Private Information and Unraveling on the Market for Lemons: An Experiment"*. This research is closely related to the one presented in the third chapter. It also addresses unraveling of privacy and it uses a similar labor-market experiment. However, the original setup is extended in two dimensions. First, we introduce employers where the previous study focuses exclusively on workers, and second, we suggest a new parameterization where the cost of revelation is reduced to a negligible degree. These two modifications allow the paper to close a gap in the literature—a gap between the study presented in chapter three and an earlier paper by Forsythe, Isaac, and Palfrey (1989). We find that the results reported in chapter three are robust in both dimensions. The predictions capture the observed behavior rather well, but there is a systematic bias towards too little revelation. In both studies, this bias is driven by workers with low productivities who do not disclose their type. This is, however, not to suggest that our modifications did not at all affect the results. Reducing the cost of revelation increases the degree of

[2] An earlier version of this study has been published as a WZB discussion paper (Benndorf, Kübler, and Normann, 2013).

unraveling dramatically. However, this increase is already captured by the theoretical predictions. Introducing employers has an inconclusive effect. In the game with employers, high-productivity workers reveal more frequently and low-productivity workers reveal less frequently. The first effect will be explained by fairness considerations which are less important in the game with employers. The second effect is driven by a bias in the behavior of the employers. Employers bid less competitively if the worker chooses to reveal. Given these wage bids, fewer workers have an incentive to disclose their private information.

A central prerequisite of the unraveling argument is that players are capable of several steps of reasoning. Typically, only the most productive workers will find it in their interest to reveal information when others conceal. However, given that the most productive players reveal, more players will reveal, and so on. Such iterated steps of reasoning are captured by the level-k model. The level-k model is popular among economists for analyses of experimental data. It was introduced by Stahl and Wilson (1995) and Nagel (1995) and its original application was to explain subjects' behavior in p-beauty-contest games. Some games such as the "20-11 money request game" have specifically been designed for the elicitation of k-levels (Arad and Rubinstein, 2012). In the fifth chapter of this thesis, we present one further approach for such an elicitation.

Chapter 5 is titled *"Depth of Reasoning in the Market for Lemons: A Note on the Distribution of k-Levels"*. The study is joint work with Dorothea Kübler and with Hans-Theo Normann. In this note, we point out than using the strategy method makes our labor-market game suitable for elicitation of k-levels. In the corresponding experiment, we observe a distribution of level-k types that is virtually identical to the one reported by Arad and Rubinstein (AER, 2012) even though there are substantial differences between the two approaches.

Chapter 2

The Willingness to Sell Personal Data

Co-authored with Hans-Theo Normann

2.1 Introduction

How people evaluate the uses of their personal data—indeed, whether they consent to the uses of such data by others at all—is important for the public policy of privacy. Currently, enterprises, governments, and scientific research institutions are investing into large, detailed data sets compiled from different sources ("Big Data"), often including individual-level personal data. At the same time, there is a growing degree of concern and unease in the population about the commercial uses of private data. An uninformed regulatory policy regarding privacy issues can cause significant welfare losses, so how people value their privacy is central.

Existing empirical studies eliciting such evaluations of privacy protection, however, suggest highly diverse results. On the one hand, some survey studies[1] suggest that a vast majority of the population are highly concerned about their personal data. These studies indicate that, for example, up 90% of the participants categorically deny any willingness to sell personal data for commercial use. Moreover, those participants who do agree in exchange for compensation make rather high demands (Acquisti and Grossklags, 2005b) which are far removed from the real value or market price of such data.[2] On the other hand, some

[1] See Office of the Australian Information Commissioner (2013) for Australia, Phoenix SPI (2013) for Canada, or Rainie, Kiesler, Kang, and Madden (2013) for the US. In section 2.4 of this study, we report in detail on a recent study for Germany.

[2] Prices for contact data at professional data brokers hardly exceed €0.50 per data set. For instance, at `http://shop.schober.com` address data from Germany is available at a

incentivized field studies indicate that very few participants are willing to pay even petty sums of money in exchange for better privacy protection (Beresford, Kübler, and Preibusch, 2012). The enormous discrepancies in the willingness to pay for privacy reported in these studies arguably limit their usefulness for policy making.

Various explanations have been proposed to explain the variance in the results of the empirical studies. Here, we discuss the most significant issues (see also: Tsai, Egelman, Cranor, and Acquisti, 2011).

First, many of the empirical studies on the valuation of privacy employ hypothetical methods like contingent valuation surveys and non-incentivized experiments. It is well known that the willingness to pay can be substantially lower in incentivized settings. Harrison and Rutström (2008) suggest a *hypothetical bias* which occurs when values that are elicited in a hypothetical context, such as a survey, differ from those elicited in an incentivized context, such as a market or auction. They review a number of studies (mainly about the evaluation of environmental goods) and find that contingent valuation surveys systematically yield higher values than those obtained in a non-hypothetical setting with monetary incentives.

Second, the questions posed about privacy often do not make clear (deliberately or not) who will use the participant's personal data and for what purpose. While this may be realistic in some situations people face in every day life and may thus be interesting for policy, it is important to note that decision makers dislike such ambiguity, and the willingness to sell personal data in such cases is reduced. Acquisti and Grossklags (2005b) emphasize the relevance of ambiguity. They report a generally low willingness to sell information (with a large proportion "never" willing to sell or willing to sell only if paid more than \$500) and that it is affected by framing effects.

Third, a lack of salience (Smith, 1982) of the privacy issue may cause the values elicited to be rather low in some studies. Specifically, field studies often avoid emphasizing that the purpose of the experiment is an elicitation of one's willingness to sell data, so the realistic field setting may effectively serve as a decoy. The "unwillingness to pay for privacy" (Beresford et al., 2012)[3] under such conditions is an important and policy relevant finding. In common situations

price of €0.24 per data set and the selection may be conditioned on several aspect (age, housing, etc.). The corresponding telephone numbers can be purchased at the same site for an additional fee of €0.13. Similar services also exist in the US. For instance, at `http://www.geoselector.com` 10,000 addresses from Californian consumers were offered for \$399.90.

[3] In their incentivized experiment, (Beresford et al., 2012) observe a rather low willingness to pay for privacy when participants can choose whether to buy DVDs in two different online stores. The stores only differ by the amount of personal information the buyer has to submit. Even when both stores charge the same price, participants do not buy significantly more often in the store requiring less information for the purchase. Perhaps, it was not sufficiently apparent to subjects that in one of the shops they had to provide more personal data.

people face every day, for example, when shopping online, privacy issues may not be salient to them and may hence be ignored. In an incentivized experiment, Tsai et al. (2011) vary the salience of the shops' privacy policies and report that increased salience triggers a preference for stores with better privacy policies. The downside of emphasizing privacy issues may be a demand effect.

Fourth, Acquisti, John, and Loewenstein (2009) find evidence of a gap between "willingness to buy" and "willingness to sell" privacy. Depending on whether subjects consider the sum of money they would pay to protect otherwise public information or the sum of money for which they would sell otherwise personal information, participants in an experiment assign significantly different values. It turns out very few people are willing to spend money to protect their data but many people would decline an offer to sell the same data for a similar price.

In our study, we elicit the willingness to sell personal data, addressing these points. We employ incentivized laboratory experiments, avoiding the hypothetical bias of non-incentivized methods. We clearly and distinctly state how the data to be bought is to be used: the data were given to a large and well-known telecommunications company for marketing purposes and would not be forwarded to third parties. As long as participants trusted this company regarding privacy issues, there was thus no ambiguity about the use of the data. Finally, we assess the willingness to sell rather than the willingness to buy the protection of personal data. For the type of information we are analyzing (contact data, Facebook details), it does not seem straightforward to design a willingness to buy experiment.

Our aim is to elicit privacy values in a transparent and incentivized laboratory setting—which is not to claim that this is the only valuable method. As mentioned above, to study an ambiguous use of the data has interesting policy implications. The same holds for field experiments where the treatment of the data is non-salient, and for contingent evaluation methods. However, we believe that an incentivized experiment where the sale of personal data is clearly the purpose of the investigation and where the first and secondary use are transparent will fill an important gap in the literature.

One novelty of our experiment is that it is, to our knowledge, the first study to elicit reservation prices for data from a social network (Facebook).[4] The data to be sold (Facebook's "About" and "Timeline" categories) contain a wealth of information not only about the participants but also about their friends and contacts. Thus, there seems to be a lot at stake here, suggesting a low willingness to sell. On the other hand, companies running social networks have been repeatedly accused of being too careless with respect to privacy issues. So one could argue that this information is sort of public anyhow. Moreover, people who have a Facebook account may be a biased sample; indeed, unreserved posting behavior

4 Stutzman, Gross, and Acquisti (2013) study whether Facebook users changed their privacy and disclosure behavior between 2005 and 2011. The authors find evidence for an increasing awareness of privacy issues among Facebook users.

on Facebook pages often serves as an example that people can be rather careless about their personal data. Either way, it seems interesting how participants evaluate data stored on Facebook. We elicit these data in a non-hypothetical, incentivized manner.

We find that only a minority of about 10% to 20% are unwilling to sell personal data, a share which is roughly constant across the type of data we ask for and the elicitation method. Subjects who are willing to sell request about €15 for their contact details and €21 for Facebook details.

2.2 Experimental Design and Procedures

We conduct a series of incentivized experiments to elicit subjects' willingness to sell personal data. We employ the mechanism proposed by Becker, DeGroot, and Marschak (1964) and take-it-or-leave-it offers.

2.2.1 The Becker, DeGroot and Marschak mechanism

The Becker et al. (1964) mechanism (BDM) is a standard way to figure out for how much an individual is willing to sell an item for. It precisely elicits an individual's willingness-to-pay for goods or lotteries, much like a second-price auction.[5]

We implemented the BDM as follows. Subjects had to state the minimum amount of money they would accept in exchange for an object they could sell to the experimenters. The valuation of the experimenters was then determined by a random draw. If this valuation exceeded the minimum price claimed by a participant, the object was sold and the subject received the randomly determined valuation as a payment. If the price claimed exceeded the valuation of the experimenters, the participant kept the object but did not receive any money.

Because the BDM procedure can be rather demanding, we made several arrangements to familiarize the participants with the mechanism. Before we elicited the subjects' willingness to sell personal data, we endowed them with a coffee mug they could sell back to the experimenters (fully incentivized). Following Grether and Plott (1979), we stressed that subjects had an incentive to state their true valuation and that renegotiations were excluded. We also clarified that the random draw was independent of actual choices. Finally, subjects also had the possibility to conduct several tests with different prices and random draws using a payoff calculator that displayed the hypothetical outcomes before making their actual choices.

In our BDM experiments subjects were told about the support of the random draw (between €0 and €50) before actually deciding on their minimum price. This is not without loss of generality. Bohm, Lindén, and Sonnegård (1997) find

[5] Karni and Safra (1987) show that the BDM is not incentive compatible when individuals are not expected utility maximizers.

that BDM-elicited valuations are sensitive to information about support. Specifically for our good (personal data), subjects may find it difficult to indicate their true valuation because a "realistic" selling price is not readily available. Information about the support may thus anchor subjects' decisions. The anchoring effect can work either way. On the one hand, we find that not too many subjects ask for more than the upper bound we imposed. This may suggest that the anchoring effect reduces some subjects' willingness to sell. On the other hand (as indicated in the introduction), realistic market prices for the kind of information we try to buy from subjects are far below €50. In that case, the anchoring effect may inflate decisions.[6] We regard the second possibility as more relevant and therefore employed the take-it-or-leave-it variant which does suggest a high but still feasible price for the data (see below).

2.2.2 The take-it-or-leave-it (TIOLI) mechanism

In the take-it-or-leave-it (TIOLI) experiments, subjects had the possibility to complete a printed form asking for personal information. Everyone who agreed to fill in the form received €5. The possibility not to fill in any forms was emphasized multiple times. In this case they did not receive €5.

The TIOLI sessions were conducted at the end of experiments that were unrelated to this study. After the unrelated experiments were completed (including payoff information), subjects were given the form and were told about the possibility of gaining an additional €5. We control for the earnings and the duration of the unrelated experiments, allowing us to detect possible wealth effects. At the end of the session, subjects were paid for the experiment they had initially participated in plus, possibly, the €5.

2.2.3 The data to be sold

In both TIOLI and BDM, subjects were asked to sell different bundles of personal information to a well-known telecommunications company. They were informed that the data would be used for market research, including marketing calls and mailings. We emphasized that the information sold would not be disclosed to other parties and that subjects could always choose not to sell any information. In this case subjects did not have to provide any information whatsoever. Moreover, subjects were made aware of the fact that they were expected to provide complete and truthful information if they did decide to accept the offer.

The experiments covered five different bundles of personal information subjects could sell. One bundle was anonymous, but the other bundles contained information that was linked to the subject's name. The following list contains a brief summary of the different data bundles used in the experiments:

[6] One alternative is to not give any information at all about the upper bound of the support. This may, however, trigger excessive bidding should subjects misunderstand the BDM.

1. **Preferences:** anonymous, contains questions on hobbies, shopping behavior, political views and income, together with questions on date of birth, gender, field of studies and/or occupation.

2. **Contact data:** not anonymous, contains questions on the subject's name, address, e-mail address, and cell phone number.

3. **Combination:** not anonymous, contains all the questions from the Preferences and Contact data bundles.

4. **Facebook About:** not anonymous, subjects are asked to sell a digital copy of their personal About page on Facebook.

5. **Facebook Timeline:** not anonymous, subjects are asked to sell a digital copy of their personal Timeline page on Facebook.

The information only had to be provided if a subject was willing to sell. This is in contrast to some experiments where the personal information has to be provided to the experimenter even if the subject is not willing to sell (e.g., Huberman, Adar, and Fine, 2005). In bundles one to three, participants were asked to fill out printed forms. The experimental procedures ensured that subjects selling one of the non-anonymous bundles stated their correct name and that the Facebook profiles carried the subject's real name. When arriving at the lab all participants had to identify themselves using their student ID card, government issued ID card, or driver's license, and the data they sold was verified as correct.

Bundles four and five had to be provided in the form of a download of some of the information stored in the subjects' personal Facebook accounts. These downloads were conducted using the standard "Save as" feature of the web browser. The data were downloaded onto the hard disk of lab computer. The downloads could not be manipulated, nor could the data be restricted in some way. The Facebook data were stored in HTML format including all pictures, etc. Note that these data sets comprise all entries from the corresponding Facebook page—even very old ones. This was demonstrated to the group of subjects at the start of the experiment in a brief beamer presentation. An actively used Facebook account was a requirement for participation in these experiments.[7]

2.2.4 Procedures

The BDM sessions followed a within-subjects design to elicit the valuations for different data bundles at the same time. There are, however, two different variations of this. In the first version, subjects sequentially state their reservations prices for the Preferences, Contact data and Combination bundles. It was made

[7] The exact requirements were: at least 50 contacts, has existed for at least one year, and is attributed the subject's real name.

clear that, in the end, only one of these bundles would be payoff relevant. Put differently, subjects were only paid to complete one of the printed forms which was selected at random. The second BDM experiment uses the same within-subjects design and tackles the Facebook About and Facebook Timeline bundles.

We conducted TIOLI offer variants for the Preferences, Contact Data and Combination bundles separately. Note that it is virtually impossible to conduct a TIOLI variant for the Facebook data because the procedure takes too long and because not all participants have a Facebook account.

<table>
<tr><th></th><th>Preferences</th><th>Contact data</th><th>Combination</th><th>About</th><th>Timeline</th></tr>
<tr><td>BDM</td><td colspan="3">89</td><td colspan="2">17</td></tr>
<tr><td>TIOLI</td><td>24</td><td>42</td><td>42</td><td>NA</td><td>NA</td></tr>
</table>

Table 2.1: Combinations of method and data bundle and the corresponding number of participants.

Table 2.1 summarizes the different combinations of experimental methods and data bundles in the incentivized experiments. All these experiments were conducted at the DICELab on the campus of the university of Düsseldorf and all sessions took less than one hour. The BDM experiments were conducted using z-Tree by Fischbacher (2007). The TIOLI sessions were done with pen and paper. Participants of the laboratory experiments were recruited using Greiner's (2004) ORSEE software. We had 214 participants in these laboratory experiments.

2.3 Results

In this section we present the results from our incentivized experiments. First, we address the BDM experiments and then the results from the TIOLI experiments are discussed. Finally, we present a brief comparison and an interpretation of these results.

2.3.1 BDM

In the BDM experiments, subjects were asked to state the minimum price at which they were willing to sell their data. They also had the possibility to flatly reject the offer by selecting an option labeled "I will not sell not on any account." Despite this possibility, several subjects entered very high prices (up to €100 million) which would inflate the average reservation price. As a consequence, we disregard all prices that exceed the €50 threshold of the random draw when calculating the mean reservation prices. For the calculation of percentiles we assume that subjects flatly refusing to sell their data have an infinitely high reservation price and include them in the calculations.

Table 2.2 shows that among most subjects there is a general willingness to a accept monetary offer in exchange for private data. The highest willingness to sell occurs for the Preferences bundle where 87 of 89 agreed to provide their data. The Contact data and Combined treatments have significantly lower willingness to sell (Fisher exact tests, all tests $p \leq 0.020$). The lowest values occur for the Combination bundle (70 of 89 subjects) and the Facebook data (15 of 17). These three bundles are not significantly different from each other (Fisher exact test $p \geq 0.160$).

	n	willing to sell	mean	median	80%ile	90%ile
Preferences	89	87 (97.8%)	8.32	5.00	15.00	35.00
Contact data	89	78 (87.6%)	14.88	12.50	40.00	100M
Combination	89	70 (78.7%)	18.90	25.00	80.00	∞
Facebook About	17	15 (88.2%)	20.88	20.00	45.00	∞
Facebook Timeline	17	15 (88.2%)	21.92	20.00	49.00	∞

Table 2.2: Summary of reservation prices under the BDM conditions. Notes: "willing to sell" is the share of participants willing to sell at a price $p \leq 50$; "∞" indicates that more than 10% of the participants are not willing to sell their data at all.

The last columns of Table 2.2 summarize mean and median reservation prices as well as some higher percentiles (the latter are included to document some of the outliers that were disregarded in the calculation of the means) for all five data bundles. The prices are lowest for the anonymous Preferences (€8.32) and highest for Combined and Facebook (about €19 to €22 on average). We find that the prices requested for Preferences are significantly lower compared to Contact data and that the prices requested for Combination are significantly higher compared to Contact data (two-sided Wilcoxon matched pairs tests, $p < 0.001$ in both cases). As for the Facebook treatments we do not find a significant difference concerning the prices requested for the About and the Timeline page (two-sided Wilcoxon matched pairs test, $p > 0.999$). The majority of the subjects chose the same price for either Facebook page.

Figure 2.1 visualizes the distributions of the reservation prices as elicited using the BDM design. The figure emphasizes the findings we reported above. For (nearly) any price the willingness to sell Contact data is higher compared to Combination and lower compared to Preferences. As for the Facebook data it can be seen that there are hardly any differences in the distributions. The functions are literally identical for many price levels.

The results regarding the Facebook treatments seem worth commenting on: 15 of 17 subjects consented to provide copies of their About and Timeline pages

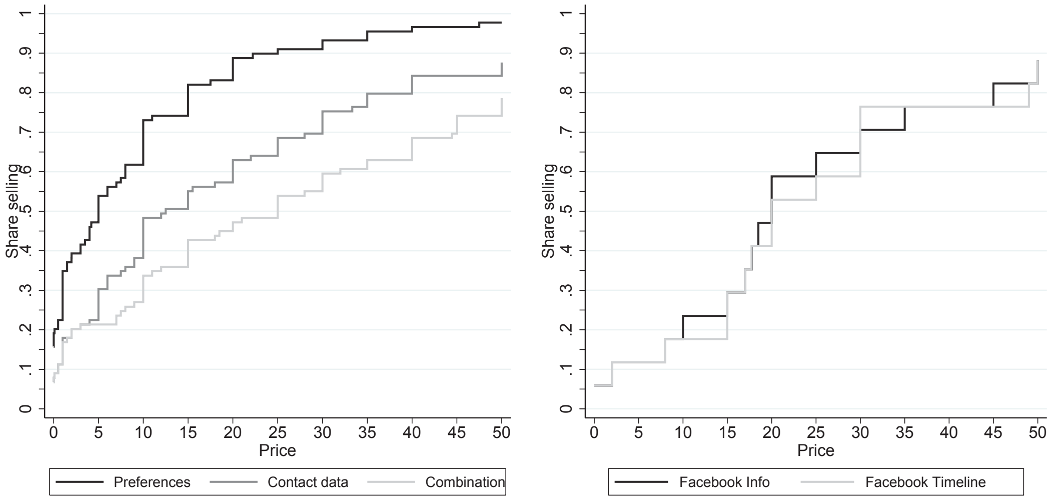

Figure 2.1: Cumulative distribution of prices for data bundles, Preferences and Contact data (left panel), Facebook data (right panel).

on Facebook. This is significantly above a 50% level suggested by randomization (binomial test, $p < 0.001$). The share of participants generally willing to sell as well the selling prices are roughly comparable to the values obtained in Combined. On the one hand, this makes sense in that both data bundles involve contact data as well as content about preferences or other personal issues. On the other hand, the Facebook bundles are much more detailed and also contain data on third parties (Facebook's "friends"). Apparently, this externality on others is ignored when selling decisions are made.

2.3.2 Take-it-or-leave-it offers

In these experiments subjects were offered a lump sum of €5 if they consented to disclose their personal data for marketing purposes. These offers were made at the end of two other, unrelated experiments that were labeled "RL" (a coordination game on cartel stability) and "P2" (a lemons market with quality certification).

Data	total	willing to sell	percent
Preferences	24	24	100.0%
Contact data	42	35	83.3%
Combination	42	35	83.3%

Table 2.3: Number of participants willing to sell their data for a lump sum of €5.

The results from the TIOLI experiment can be seen in Table 2.3. We find that all participants accepted the offer for the anonymous Preferences data bundle whereas the Contact data and Combination bundle were accepted by 35 out of 42 subjects. The rate for Preferences is significantly different from the other two treatments (Fisher's exact test, $p = 0.042$). This is also captured by the probit regressions in Table 2.4 where the dummy variables for Contact data and Combination are significantly negative.

	(1) sold data	(2) sold data	(3) sold data
Payoff	-0.0986	-0.0876	-0.0970
	(0.0827)	(0.0780)	(0.0793)
Contact data		-4.507***	-4.556***
		(0.325)	(0.413)
Combination		-4.498***	-4.544***
		(0.220)	(0.215)
Experiment "P2"			0.254
			(0.262)
Constant	2.951*	7.089***	7.211***
	(1.537)	(1.440)	(1.467)
Observations	108	108	108

Standard Errors adjusted for 8 clusters (sessions)
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2.4: Probit regressions on TIOLI acceptance.

How about possible spillovers from the experiments preceding the TIOLI sessions? The probit regressions outlined in Table 2.4 analyzes the TIOLI decisions controlling for such effects. The dependent variable is a dummy indicating whether or not the subject sold the data. "Contact data" and "Combination" are dummies for the corresponding bundles. We control for wealth effects and other aspects that might vary across these experiments (e.g., the duration of a session, number of participants per session). "Payoff" captures the subject's earnings from the experiment she participated in and the different experiments are identified by a dummy variable for Experiment "P2". The dummies Contact data and Combination control for the data bundle the subject was asked to disclose. We find that neither Payoff nor Experiment "P2" have a significant impact on the inclination to sell data. Hence, there are no wealth effects in our data and also the differences between the two experiments do not affect subjects' disclosure decisions.

2.3.3 Comparison

Figure 2.2 displays the acceptance rates in TIOLI and BDM for the three data bundles that were considered in the TIOLI treatments. We include two data series from the BDM treatment: the share of subjects willing to sell their data for €50 and the share of subjects willing to sell their data for €5. These shares also include all subjects with lower reservation prices. The data series are referred to as "BDM-50" and "BDM-5", respectively. The TIOLI data depicts the share of subjects that accept the €5 take-it-or-leave-it offer.

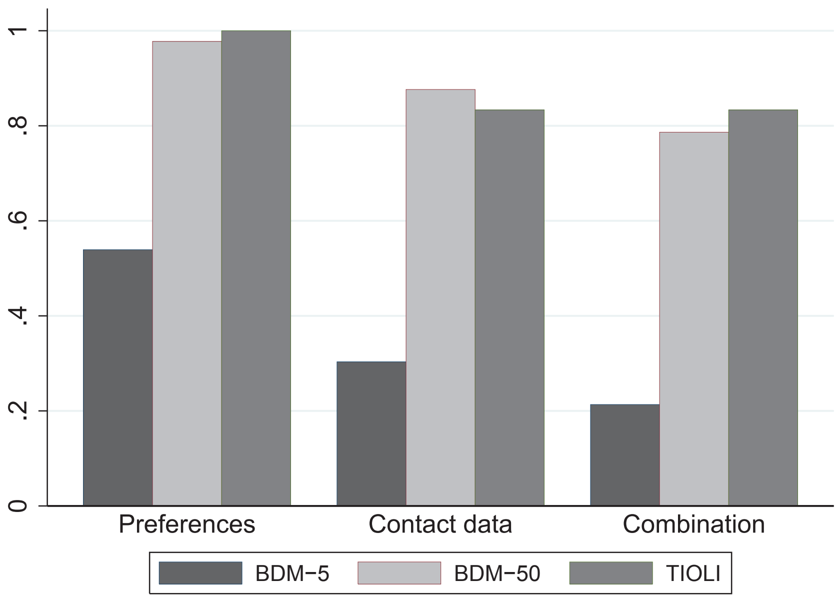

Figure 2.2: Comparison of the share of subjects willing to sell information across treatments and data bundles.

We find that the share of subjects who agree to sell their data for €50 in BDM is virtually identical to the share of subjects that accept the €5-TIOLI offers. That is, the share of subjects who are in principle willing to sell their data is the same. In both treatments nearly all participants hand over their Preferences data. For Contact data and Combination where about 75% to 80% are willing to sell in both treatments. None of these differences are significant (two-sided Fisher's exact tests, $p > 0.999$, $p = 0.558$ and $p = 0.642$ for Preferences, Contact data and Combination, respectively).

Having said that, the TIOLI offers are accepted more frequently than suggested by the "BDM-5" data where far fewer subjects were prepared to sell their data for €5. For instance, while literally all subjects accepted the TIOLI offer for the anonymous Preferences bundle only about 53.9% would have sold the same data for the same price in "BDM-5". Figure 2.2 documents that the same pattern applies for Contact data and for Combination. The willingness to sell for €5 is significantly lower in "BDM-5" compared to TIOLI (two-sided Fisher's exact tests with $p < 0.001$ in all three cases).

2.4 Survey

We also have access to data from a non-incentivized survey on the German population's attitude toward privacy issues.[8] It addressed a representative sample of the German population. In total 460 males and 540 females aged between 18 and 94 were questioned via telephone interviews. Note, that their answers were weighted in order to achieve representative results and that subjects were not paid for their participation.

Sample	all	young
Contact data such as address or telephone number	7.27%	12.09%
Personal information such as sex or birthday	6.62%	11.83%
Data like the one in social networks	4.50%	12.47%

Table 2.5: Disposition to provide personal data for commercial uses when being paid (hypothetically).

Some of the survey questions were directly related to the decisions subjects had to make in our incentivized experiments and can therefore be used as a benchmark for our experimental findings. Here, subjects were asked whether or not they would agree to a commercial use of their data if they received a monetary remuneration in exchange. Table 2.5 lists the share of subjects indicating their consent for different sorts of data. The column "All" refers to the entire representative sample whereas "Young" only includes the answers of the 18 to 29-year-olds. We include this differentiation since about 90% of the participants in the incentivized experiments were between 18 and 29 years old.

In the non-incentivized survey subjects show very little disposition to sell their data for commercial uses. Only about 12% of the 18 to 29-year-olds give their consent for all data bundles. This is in strong contrast to the behavior we observe in our incentivized experiments where a vast majority of the participants agreed to sell the same data for commercial usage (see Figure 2.2). In fact the shares are even pretty much reversed.

2.5 Conclusion

In this paper we elicited subjects' valuations for privacy in a controlled laboratory experiment. We use a Becker et al. (1964) mechanism (BDM) and take-it-or-leave-

[8] See Forsa (2013) for a description of the data. Forsa, a well-known German research company, gave us access to the raw data.

it offers (TIOLI) to elicit values. Our experiments were fully incentivized in order to avoid a hypothetical bias. The purpose of the data acquisition was transparent to our participants. There was no ambiguity about the use of the data. Finally, the focus of the experiments—privacy—was salient.

We find that about roughly five of six participants are willing to sell personal data for commercial usage. This share is constant across both our treatments. In TIOLI these participants sold their data for €5. In the more sophisticated BDM design we elicited participants' precise reservation prices. Here, subjects requested on average €15 for their contact data and about €21 for detailed information from their personal Facebook accounts.

At the same time there is a minority of roughly one in six participants who persistently refuse to sell personal data. This share is also roughly constant across our treatments. The corresponding participants do not fall for the take-it-or-leave-it offers and in BDM they waive up to €50 to keep their data private. This suggests that these subjects have a truly high valuation for privacy.

A comparison of the BDM and TIOLI results yields an additional interesting insight. The share of participants willing to sell for €5 or less in the BDM sessions is significantly smaller than the share of subjects selling in the €5 TIOLI variant. This suggests that the elicitation method has an impact on valuations. Bohm et al. (1997) also made this point regarding different BDM variants.

We find evidence for a hypothetical bias that occurs when privacy attitudes are researched using non-incentivized methods. Recent survey data we analyze suggests that a vast majority (about five in six people) has strong concerns for privacy issues and that very few people would disclose private data in exchange for money. However, our incentivized experiments show the exact opposite. This discrepancy has long been labeled "privacy paradox" (see Syverson, 2003).

Last but not least, our experiment is the first to analyze the willingness to sell data from a social network (Facebook). The share of participants generally willing to sell, as well as the selling prices, are roughly comparable to the values obtained when we elicit contact details plus personal preferences. However, the Facebook data also contain information on third parties (Facebook's "friends"). It appears that participants ignore this externality on others. While this would be consistent with standard (non-other-regarding) preferences, this attitude would be worrisome from a policy perspective that is concerned about the protection of data.

The conclusions we can draw from this paper are not unambiguous. On the one hand, policy makers should probably not rely on purely hypothetical data when evaluating privacy issues since there is a substantial bias in such data. Many people exaggerate their true valuation for privacy in hypothetical setups because stating a high valuation does not come at a cost. A regulatory policy relying on hypothetical studies may be biased as a result, too. On the other hand, there is a persistent minority who have considerable concern for privacy. Since these people demonstrate substantial valuations for privacy, their potential losses may therefore outweigh the potential gains from policies that come with a reduction of their privacy.

2.A Instructions/Procedures for BDM

This section describes the instructions subjects were given for the BDM experiments. Unlike other experiments the instructions were not distributed as printed handouts but were presented on the participants' computer screens as a part of the z-Tree program. Additional information was given via oral announcements. In the following we describe these announcements as well as the text that was displayed on subjects' screens in the course of the experiment.

Screen 1: *Information screen for the mug. A picture of the mug was displayed but we also distributed some samples of the mug such that subjects could examine it. We did, however, collect the samples before subjects made their decisions.*

The first part of the experiment is about a coffee mug you will get from us. You will have the opportunity to sell the mug back to us. You can see a picture of the mug below. The selling procedure works as follows: On the next pages you will be asked to enter the minimum price at which you are willing to sell the mug. The actual price will be determined by a random draw of the computer. If this random draw is lower than the price you have entered, you will keep the cup. If it is higher you need to return the mug to us and we will give you the price in cash as determined by the random draw. Please note that it does not make sense to enter prices exceeding your true valuation. By doing so you will only lose money. If your valuation of the mug is for instance €1, you should enter €1 as your reservation price. If the random draw decides that we pay a price of €4, you will receive €4 even if the reservations price you entered was only €1. However, if you have entered a reservation of €5 you will keep the cup and not receive any money at all.

Screen 2: *Simulation screen. Here, subjects received additional information orally. For instance, that subjects' decisions would be final and that no renegotiations would take place. We also emphasized that the randomly determined price was independent of subjects' reservation prices. The screen contained a repetition of the description of the selling procedure from Screen 1 and the following text:*

Simulator: Here you can simulate the selling process of the mug. Below, you can enter different reservation prices. Whenever you click the "simulate" button the computer will perform a random draw determining a hypothetical price. On the right-hand side you will see whether or not you would have sold the mug and how much money you would have earned. These simulations are completely hypothetical and do not affect your payment. Note that we will certainly not pay more than €8 for the mug.

Screen 3: *Decision screen for the mug. Subjects were presented with an input field to enter their minimum price but they were also given the possibility to check an option "I will not sell not under any account". If this option was checked* *no price could be entered. Once again we emphasized that the decisions were final and that no renegotiations would take place. We stressed that the support of the random draw was inbetween €0 and €8 and that the random draw was independent of the prices subjects were about to enter.*

Please make your actual decision now. Below you can enter the minimum price at which you are willing to sell the mug. Note that we will not pay more than €8.

Screen 4: *Result screen for the mug. Screen 4 was summarized the result of the random draw, repeated the subject's decision, and displayed whether or not the subject had sold the mug.*

Screen 5: *End of part 1. Here subjects were informed that the process of selling the mug was only conducted to familiarize them with the selling procedure and that the actual experiment was about their privacy attitudes. We stressed that the data sold would actually be transmitted to [name of the company] and that market research also covered marketing actions. The different forms were distributed to the subjects to make sure they knew what kind of data they were supposed to sell. We emphasized that subjects were expected to fill in all the fields of the corresponding form and that their answers had to be truthful.*

Market research: [name of the company] would like to purchase some personal data of yours for the purpose of market research. More precisely, there are three different printed forms one of which you will need to complete if you decide to sell the corresponding information.

- The first form contains questions concerning: gender, date of birth, field of studies/occupation, hobbies, income, political attitude and buying habits. This form is anonymous. The data will not be linked to your name.
- The second form contains questions concerning your contact information: Name, address, mobile number and email address. This form is not anonymous.
- The third form is a combination of the first two forms. This form is also not anonymous.

On the following pages you can determine the minimum price you request for selling your data to [name of the company]. [name of the company] will not disclose your data to any third parties. You have full control over your data during the entire experiment. If you do not sell your data no data whatsoever will be transmitted. However, if you decide to sell your data you will receive the corresponding payment in cash at the end of the experiment. At the end of the experiment a random draw of the computer will determine which form is relevant for the payment. Only one of the three forms will be transfered to the [name of the company]. Therefore, you have to fill in one form at most.

Screen 6: *Information screen for form 1.*

Please determine your reservation price for completing form 1 and selling it to [name of the company] for the purpose of market research. Form 1 concerns details about gender, date of birth, field of studies/occupation, hobbies, income, political attitude and buying habits. There will be no linkage to your name. The data remains anonymous. The selling procedure is identical to the one for the mug. You should enter the minimum price at which permit us to transfer the above mentioned data to [name of the company]. The actual price will be determined by a random draw of the computer. If this random draw is lower than the price you have entered, we will not transfer your data. If it is higher, [name of the company] will receive your data and you will receive the price in cash. Please note that it does not make sense to enter prices exceeding your true valuation. By doing so you will only lose money. Note that we will certainly not pay more than €50 for this data package. [name of the company] will not disclose your data to any third parties. You have full control over your data during the entire experiment. If you do not accept a transfer, no transfer will take place.

Screen 7: *Decision screen for form 1. Analogous to Screen 3 except for the reference to the mug and the support of the random draw.*

Screen 8-11: *Information and decision screens for the forms 2 and 3. Analogous to screens 6 and 7 but emphasizing that the data to be sold was not anonymous.*

Screen 12-13: *Screens summarizing the results of the random draws and participants payoffs from the experiment.*

The experiments concerning the Facebook data were conducted analogously. The screens 1 to 4 were literally identical to the ones described here. The remaining screens and announcements referred to the Facebook pages instead of the printed forms. The corresponding information screens contained screenshots of the Facebook pages that were taken from a fake account of the experimenters. Moreover, subjects were asked to open a web browser and log into their own Facebook account to get an impression of the data they were about to sell. It was emphasized that these downloads would also contain all pictures etc. and that we would store the entire pages including the very first entries of the corresponding account.

Chapter 3

Privacy Concerns, Voluntary Disclosure of Information, and Unraveling: An Experiment

Co-authored with Hans-Theo Normann and with Dorothea Kübler

3.1 Introduction

Privacy concerns and the treatment of personal data are at the center of current policy debates.[1] With the rise of digital data processing and the increased communication of information via the Internet, a wealth of personal data can be accumulated and distributed at low cost. As a result, private enterprises and governmental institutions alike face new challenges of how to adequately handle the private data of their citizens and clients.

Situations where subjects *voluntarily* disclose private information are regarded as increasingly important. For example, prospective tenants or job applicants often voluntarily disclose verified personal information. In the US, online services such as MyBackgroundCheck.com provide verified information on drug tests, criminal records and previous rental addresses to prospective landladies or em-

[1] To quantify this statement, we conducted a Google Books Ngram Viewer comparison of several keywords and compared them to the term "privacy concerns". We found that the use of the term "privacy concerns" in the English literature has been increasing steadily since the Seventies. This is in contrast to other topics like "nuclear threat" (in decline and nowadays occurring less frequently than "privacy concerns") or "racial discrimination" (more frequent than "privacy concerns", but also in decline).

ployers.[2] New-generation passports and identity cards often contain biometric data, which can be optional. And health or pregnancy tests are often voluntarily provided to existing or future employers.[3] A large part of the policy debate seems to regard it as relevant for privacy, whether people can freely agree to include the sensitive information or not.[4]

The examples illustrate that the disclosure of personal information can raise privacy concerns due to unraveling effects even when it is voluntary. In a world where credible signals can easily be obtained and distributed, these signals will be used by those with the best medical records, credit scores, etc. This may put pressure on others to disclose similar information about themselves because not disclosing will be interpreted as a signal of low quality. Thus, granting people the right to decide whether to disclose can be less of a voluntary choice than it seems at first sight. Or, as Posner (1998, p. 103) succinctly puts it "*As for privacy in general, it is difficult to see how a pooling equilibrium is avoided in which privacy is 'voluntarily' surrendered, making the legal protection of privacy futile.*"

The importance of the unraveling argument is also reflected in the legal debate. Peppet (2011) summarizes the legal perspective and argues that the voluntary disclosure of private information is crucial because of unraveling effects. The challenge to regulating voluntary disclosure is that there are always some agents in whose interest it is to disclose their information. Limits to inquiry that forbid an uninformed party from seeking information from an informed counterpart may not be sufficient as the informed party might feel that it is in her interest to disclose the information. A means to avoid unraveling may be to completely forbid the use of certain information, as for example in the *Genetic Information Nondiscrimination Act* (GINA) passed in 2008 in the US to prohibit the use of genetic information by insurers.

We study the voluntary disclosure of information in a laboratory experiment with the help of a *revelation game*. In a labor market with a lemons structure (Akerlof, 1970), workers can truthfully reveal their productivity at a positive cost. Rational revelation imposes an externality on others because it lowers the wage paid to other workers. Complete unraveling occurs when all workers reveal—except for the one with the lowest productivity who is then identified by the fact that she does not reveal her type. Our research questions are to what extent subjects reveal their productivity and whether these choices are in line with the equilibrium predictions. We further investigate how revelation choices depend on

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[2] Connolly (2008) explicitly advises applicants in the job market to use such online services (pp. 59-60).

[3] Some of Apple Inc. suppliers screened their workers with health and pregnancy test (Apple Inc., 2012). See also New-York Times, January 26, 2012. The unraveling argument suggests that whether workers voluntarily agreed to take the tests is immaterial. Further examples, discussed in Peppet (2011), include car insurance policies or rental car contracts where drivers can voluntarily agree to have the car monitored with GPS-based systems.

[4] See Curtis (2006) for the debate in Australia, Acharya and Kasprzycki (2010) for Canada, Probst (2011) for Germany, Grijpink (2001) for the Netherlands.

the productivity of the worker, on the characteristics of the market, and on the contextual framing of the choice.

In the 1980s, there was a surge of theoretical interest on the voluntary disclosure of information, but this literature has largely ignored the case where revelation comes at a positive cost (see our survey below). Such costs may be considered as a payment to external specialists who conduct the actual certification, or alternatively, they might be interpreted as an opportunity cost. This does not only appear realistic in some cases, it also allows for a richer outcome space: not all players reveal their type in equilibrium. With zero revelation costs, revealing is always rational and there cannot be any mistaken revelation decisions. In contrast, if the costs of revelation are strictly positive, the share of workers who reveal depends on the revelation cost and the distribution of productivities. Depending on these parameters, there may be equilibria with complete unraveling, with partial unraveling, or with no unraveling at all.

Despite its relevance in the privacy debate, we found only one related experiment on unraveling behavior. Forsythe et al. (1989) study a "blind bidding" auction where sellers can reveal the quality of their product. Our experiment analyzes a similar decision problem in an altogether different, namely privacy-relevant setting. Our experimental markets have strictly positive revelation costs and we implement three different variants where either a high, a medium or a low degree of unraveling should occur according to the theory. We focus on the revelation decisions of the workers (sellers) only: employers (buyers) are not represented by laboratory participants, so all potential results are driven by the behavior of the workers—which is what we are interested in. Including employers in our experiments would come at the expense of adding another source that might confound unraveling.

Our results are as follows. The equilibrium predictions for the three markets capture the differences in observed aggregate revelation rates across these markets well. We observe a significant amount of unraveling. At the same time, we find that revelation rates are somewhat lower than the equilibrium prediction in two of the three markets. Workers who are supposed to reveal their productivity in equilibrium fail to take the equilibrium choice significantly more often than workers who should conceal. We will argue that this pattern is consistent with behavioral models such as the level-k rationality model.[5] Finally, we find a statistically and economically significant framing effect: there is more revelation in the

[5] The level-k model was introduced by Stahl and Wilson (1995) and Nagel (1995). Its original application was to explain subjects' behavior in p-beauty-contest games (compare, for example, Bosch-Domenech, Montalvo, Nagel, and Satorra, 2002; Kocher and Sutter, 2005; Brañas Garza, Garcia-Muñoz, and González, 2012, for some other studies of this kind). Further applications include private-value auctions (Crawford and Iriberri, 2007) or centipede games (Kawagoe and Takizawa, 2012; Ho and Su, 2013). Some games such as the "20-11 money request game" have specifically been designed for the elicitation of k-levels (Arad and Rubinstein, 2012; Lindnera and Sutter, 2013). Extensions of the model have been developed by Camerer, Ho, and Chong (2004) and Goeree and Holt (2004).

neutrally framed sessions. Thus, it appears that the labor-market-health frame triggers privacy concerns.

Taken together, our results confirm the concerns about voluntary revelation raised in the privacy debate. We observe robust revelation rates, suggesting this behavior is likely to occur in voluntary disclosure regimes in the field where incentives for revelation may be even stronger (see our Conclusion). Such effects should be considered in the context of privacy policies involving free choice.

In the next section of this chapter, we review the relevant literature. Section 3 introduces the revelation game and Section 4 the experimental implementation and the different treatments. Section 5 reports on the results. Section 6 investigates reasons for the behavioral patterns we observe and Section 7 concludes.

3.2 Related Literature

Following the introduction of the lemons problem by Akerlof (1970), the costly but truthful revelation of private information—the certificate solution to the lemons problem—was suggested by Viscusi (1978). Subsequently, it was shown by Grossman and Hart (1980), Grossman (1981), Milgrom (1981), Jovanovic (1982), and Milgrom and Roberts (1986) that taking no action (not acquiring a certificate) may reveal an agent's type when other agents have an incentive to disclose information. Specifically, they pointed out that complete unraveling will result when revelation costs are negligible.

More recently, Hermalin and Katz (2006) investigated the impact of privacy regimes on consumer and producer rents in markets with price discrimination, taking into account unraveling effects. They argue that markets may be ex post efficient due to unraveling. However, laws banning unraveling can improve welfare ex ante because the socially wasteful revelation costs can be avoided.

While information disclosure has received much attention in the theoretical literature, only Forsythe et al. (1989) have studied unraveling in an experiment.[6] They study a game where sellers have superior information about the good compared to the buyers and can decide whether to reveal this information. The game has multiple Nash equilibria. Full unraveling in the sense of sellers disclosing

[6] There is also an empirical literature on the topic based on field data. Jin (2005) reports evidence on incomplete unraveling among Health Maintenance Organizations which may disclose information on the quality of their services on a voluntary basis. As for mandatory disclosure Jin and Leslie (2003) find that the introduction of hygiene quality grade cards for restaurants increases the consumers' sensitivity for hygiene issues in restaurants. More recently, Lewis (2011) pointed out that a lack of (voluntarily provided) ex-post verifiable information on used cars (photos, text hinting at rust, scratches, etc.) has a negative influence on the selling price in internet auctions. When such information is not easily verifiable (e.g., baseball trading cards), Jin and Kato (2008) show that cards of alleged high quality trade at substantially higher prices although their actual quality is not distinguishable compared to other cards.

their private information about the good takes place in the unique sequential equilibrium, which experimental subjects learn to play in the course of several rounds of play. Our game differs from the one in Forsythe et al. (1989) in several aspects. As mentioned above, we introduce strictly positive revelation costs and exclude buyers from participation in the experiments. Also, our game has a unique equilibrium with partial unraveling.

Our experiments have some bearing on the question of how people make choices regarding their personal data. To our knowledge, we are the first to study the unraveling of privacy experimentally.[7] Related to our framing treatment, there is a study on the framing effects of defaults used in electronic commerce for various privacy settings, see Johnson, Bellman, and Lohse (2002). Experiments have also been used to investigate decisions regarding personal data. When making purchasing decisions, consumers have been found to provide personal data freely, even when it is relatively easy and costless to avoid it (see Acquisti and Grossklags (2005a) and Beresford et al. (2012)). This behavior in combination with a strong concern for privacy protection voiced in surveys has been called the "privacy paradox".

In an experiment on information acquisition and revelation by Schudy and Utikal (2012), the impact of different data security schemes on information acquisition is investigated. In the experiments, subjects can acquire the results of a binary test (for example, an HIV test). The data security regimes are perfect privacy (no one but the testee gets to know the test result), imperfect privacy (there is a 50% chance that the results of the test will be leaked to a player interacting with the testee), and automatic dissemination where the test results are automatically disclosed to both players in a group. The authors find that taking a test that is, information acquisition, is almost complete whenever there is some data security. The only treatment with incomplete information acquisition is the one with the automatic dissemination of the test results.

3.3 The Revelation Game

Our design is based on a labor market with a lemons structure. There are $n \geq 2$ workers with $n \in N$. Worker i has productivity θ_i. Let $\Theta = \{\theta_1, \theta_2, ..., \theta_n\}$ and assume w.l.o.g. that $\theta_1 \leq \theta_2 \leq ... \leq \theta_n$.

All n workers simultaneously choose between two actions, to *reveal* or to *conceal* their productivity. Revelation causes a cost of $c > 0$ and correctly reveals the worker's productivity. Let $I_i \in \{0, 1\}$ be a function indicating whether worker

7 Signaling games are broadly related to the revelation game we study. The experimental literature on signaling includes early contributions like Miller and Plott (1985), Brandts and Holt (1992), Potters and van Winden (1996), and Cooper, Garvin, and Kagel (1997), and more recent papers like Kübler, Müller, and Normann (2008), Cooper and Kagel (2009) and de Haan, Offerman, and Sloof (2011).

i has chosen to reveal her productivity, with $I_i = 1$ denoting revelation and $I_i = 0$ concealment.

Workers' payoffs are determined as follows. If worker i chooses to reveal, i earns her productivity minus the revelation cost. If not, she receives the average productivity of all workers who have chosen not to reveal. Formally, i's payoff is:

$$\Pi_i = \begin{cases} \theta_i - c & \text{if } I_i = 1 \quad (\textit{reveal}) \\ \sum_{j=1}^{n}(1 - I_j)\theta_j / \sum_{j=1}^{n}(1 - I_j) & \text{if } I_i = 0 \quad (\textit{conceal}). \end{cases}$$

These payoffs can be thought to arise in a competitive labor market where two or more employers bid for workers and earn the workers' (expected) productivity. The employers in this labor market would know the set Θ, that is, they would know the n payoff functions of the n workers, but do not know which worker has which payoff function. Employers would earn an expected payoff of zero.

Since we exclude the employers from our analyses, this is a static game with complete information and the appropriate equilibrium concept is Nash equilibrium. See Chapter 4 for an incomplete-information game where the employers are included. Note that the proof of the following proposition can be found in Appendix B.

Proposition 1. *In any pure strategy Nash equilibrium of the revelation game, we have* $I_n^* \geq I_{n-1}^* \geq ... \geq I_2^* \geq I_1^* = 0$.

The proposition has two implications. First, there is a sorting effect in that $I_i < I_j$ for $i > j$ is impossible: revelation decisions are monotonic in productivity. Second, at least worker 1 (and possibly more) workers conceal in equilibrium. Here, the positive revelation cost in our model leads to interesting departures from the previous literature. For $c = 0$, our model also suggests that all players (except for the worker with the lowest productivity) reveal. For $c > 0$, the proposition allows for the pattern of equilibrium actions $I_1 = I_2 = ... = 0 < I_m = ... = I_n = 1$, with $1 < m \leq n$. Accordingly, in our markets described below, the model predicts several low-productivity workers to conceal.[8]

Furthermore, multiple equilibria can also exist when $c > 0$. To characterize the conditions under which there is a unique equilibrium, the following definition is helpful:

Definition 1. *Let* $\bar{\theta}(s) = \frac{1}{s}\sum_{i=1}^{s}\theta_i$. *Further, define* $C = \left\{i | \theta_i - c \leq \bar{\theta}(i)\right\}$ *and* $R = \left\{i | \theta_i - c \geq \bar{\theta}(i)\right\}$.

In words, $\bar{\theta}(s)$ is the average of the productivities of all workers $1, 2, ..., s$. The set C contains all workers whose best-response is to conceal given that all

[8] When revelation costs are prohibitively high, no player reveals, that is, $I_1 = I_2 = ... = I_n = 0$. This case can be excluded whenever $\theta_n - c \geq \sum_j \theta_j / n$.

workers with lower (higher) productivity conceal (reveal). And R is the set of all workers whose best-response is to reveal given that all workers with lower (higher) productivity conceal (reveal). When $c = 0$, $\theta_i - c \geq \bar{\theta}(i)$ holds for all i, so that all workers reveal in equilibrium.

Proposition 2. *The revelation game has unique pure strategy equilibrium if and only if* $max(C) < min(R)$.

See the Appendix for a proof. Note that while the games we use in our experiment all have a unique pure strategy equilibrium, it is easy to construct cases with multiple equilibria with the help of the proposition.[9]

3.4 Experimental Design and Procedures

In each of our experimental markets, there are $n = 6$ workers. We design three different markets, A, B, and C, with different realizations of Θ. The cost of revelation, c, always equals 100 experimental currency units; it does not vary across workers, markets or treatments. The different productivities in each market are reported in Table 3.1. The entries in bold type indicate that the corresponding subject reveals her productivity in equilibrium.

Productivity	Market A	Market B	Market C
θ_1	200	200	200
θ_2	210	**448**	280
θ_3	230	**510**	360
θ_4	260	**551**	**440**
θ_5	300	**582**	**520**
θ_6	**600**	**607**	**600**

Table 3.1: Workers' productivities in the three different markets. Entries in bold face indicate that the player reveals in equilibrium ($I_i = 1$).

The three markets are played on a rotating basis. In period 1 subjects play Market A, in period 2 they play Market B, and in period 3 Market C is played before they start all over again with Market A. Each market is played five times, totaling 15 periods altogether.

At the beginning of the experiment, subjects were randomly allocated into groups of six, and they stayed in their group for the whole experiment (fixed matching). The productivities θ_i, expressed in experimental currency units, were

[9] Suppose $n = 3$, $c = 100$, $\theta_1 = 200$, $\theta_2 = 402$ and $\theta_3 = 403$. We have $\bar{\theta}(1) = 200, \bar{\theta}(2) = 301$ and $\bar{\theta}(3) = 335$. Therefore, $C = \{1, 3\}$ and $R = \{2\}$. There are multiple equilibria: in one pure strategy Nash equilibrium, all workers conceal and we have $\theta_i - c < 335$ for $i = 1, 2, 3$; in a second pure strategy Nash equilibrium, workers 2 and 3 reveal and we have $\theta_1 - c < 200$, $\theta_{2,3} - c > \frac{200+\theta_{2,3}}{2}$.

randomly assigned to the workers in each period. The instructions emphasized that this allocation of productivities was without replacement such that each productivity value occurs exactly once in each group and in each period.

The Nash equilibrium for the three markets is as follows. In Market A, only worker 6 reveals her productivity. That is, we have $I_6 = 1 > I_5 = ... = I_1 = 0$ in equilibrium. In Market B, all workers except for worker 1 reveal: $I_6 = ... = I_2 = 1 > I_1 = 0$. Finally, in Market C, we have $I_6 = I_5 = I_4 = 1 > I_3 = I_2 = I_1 = 0$. The motivation for employing Markets A to C is that we need qualitatively different equilibrium outcomes to be able to infer whether there is too much or too little revelation. For example, Market B may show that subjects reveal too little, but given that almost all workers should reveal in equilibrium, we need to contrast this with Market A where only one of six workers reveal in Nash equilibrium.

We consider two treatments:

1. The baseline treatment, called LOADED, is based on the revelation game described in the previous section with one peculiarity. It employs a loaded labor-market frame. Subjects are told that they are acting as *workers* in a *labor market*. Their productivity is referred to as their *health status*, and subjects are told that they need to decide whether or not to *buy a health certificate*.

2. In our second treatment, NEUTRAL, we remove the labor market frame. The productivity is called *number* and the decision is merely between *yes* and *no*. The neutral treatment is implemented in order to control for the possibility of subjects' privacy concerns elicited by the framing. If the subjects care for privacy, there should be more revelation in this treatment compared to the baseline treatment with the loaded frame.

The feedback given to the participants at the end of a period was as follows. In all sessions, subjects were informed of their own profits and the market wage of that period. In 11 groups of the LOADED treatment, we gave the subjects additional information about the choices of all six workers in the group. Our hypothesis was that the additional feedback would support learning. However, we do not find any impact of the additional feedback whatsoever (see Section 3.5.3 for an analysis of learning effects). For most of the paper, we therefore ignore the differences in feedback in the LOADED treatment and pool the data.

As an aside (but one that is important for the interpretation of the results) we note that several features of the experimental design suggest that there might be more unraveling in the field compared to our laboratory setting. First, the simultaneous move structure necessitates players to anticipate the decisions of the other market participants. In contrast, in a sequential setting unraveling occurs even if players are only myopically best responding to the choices of others. Second, our groups of six players are matched together for the entire experiment consisting of 15 rounds. Cooperation (in the sense of joint payoff maximization)

	LOADED_BASE	LOADED_FEED	NEUTRAL	Σ
detailed feedback	no	yes	no	
participants	72	66	66	204
indep. groups	12	11	11	34
sessions	3	3	3	9
groups per session	4	3-4	3-4	

Table 3.2: Treatments.

would induce them to conceal their type to save on the revelation costs, again making unraveling less likely. Field settings may, by contrast, often be of a one-shot nature. Finally, in our experiment the productivity of the workers is not attained by merit, but assigned randomly. Revelation might increase if workers feel entitled to a higher wage because they have invested in their productivity.

The experiments were conducted between July and September 2011 at the experimental lab at the Technical University Berlin, using the z-Tree software package by Fischbacher (2007) and Greiner's (2004) on-line recruitment system. In total, 204 subjects participated in the experiment, a session lasted around 60 minutes, and subjects earned between 8.19 € and 12.51 €. The average payment was 10.70 €. More details on the number of participants and the independent observations gathered in this experiment can be found in Table 3.2.

3.5 Results

3.5.1 Main Findings

This section gives an overview of the participants' decisions and shows how these decisions relate to the equilibrium predictions. We will also explore the differences between the treatments LOADED and NEUTRAL. We mainly use non-parametric tests where we conservatively count each group of six players as one independent observation.

Our first research question is to what extent subjects reveal their productivity at the market level. Table 3.3 displays the relevant revelation rates per market and across all three markets, averaged across the six workers and all periods. It turns out that subjects choose to reveal their productivity often. Taking all markets together, 41.4% and 36.6% of the subjects do so in NEUTRAL and LOADED, respectively, compared to the 50% prediction.

The equilibrium predictions for the three markets separately also capture the differences in observed revelation rates rather well. As in equilibrium, we observe more revelation in Market B than in Market C, and there is more revelation in C than in A.

Observation 1. *In all markets and all treatments, we observe substantial levels of revelation. The differences between markets are well organized by the predictions.*

Whereas prediction and behavior are rather accurate in Market A, too little revelation compared to the prediction is observed in Market B, especially for LOADED. Using a sign test, revelation rates are significantly below the prediction in Markets B and C of both LOADED and NEUTRAL (two-sided tests, all $p < 0.05$). Having said that, the difference is small in Market C in the NEUTRAL treatment.

	All Markets		
	equilibrium	LOADED	NEUTRAL
reveal	0.5	0.360	0.414
(std. dev.)		(0.082)	(0.048)
	Market A		
	equilibrium	LOADED	NEUTRAL
reveal	0.167	0.188	0.176
(std. dev.)		(0.068)	(0.037)
	Market B		
	equilibrium	LOADED	NEUTRAL
reveal	0.833	0.530	0.618
(std. dev.)		(0.155)	(0.108)
	Market C		
	equilibrium	LOADED	NEUTRAL
reveal	0.500	0.361	0.448
(std. dev.)		(0.094)	(0.062)

Table 3.3: Revelation rates (market average across all six workers). Standard deviations (in parenthesis) are calculated using group averages.

We next study the equilibrium consistency of choices at the individual level. Table 3.4 reports the results of probit regressions (clustered at the group level) with *Consistency* as the dependent variable. *Consistency* indicates whether a subject behaves in line with the Nash prediction. The dummy variable *Reveal* indicates the equilibrium action of the corresponding subject (*Reveal* = 1). The dummy for the treatment with the loaded frame is *Loaded*, and *Period* captures possible time trends. The dummy variables *Market A* and *Market B* represent departures from the (baseline) Market C in the regression.

Considering the different markets, the regressions in Table 3.4 confirm that there are more equilibrium choices in Market A and fewer equilibrium choices in Market B compared to Market C. More importantly, we observe a tendency to reveal less than predicted. The frequencies of out-of-equilibrium revelation and concealment decisions differ. The regressions show that *Reveal* has a highly

Consistency	(1)	(2)	(3)
Reveal	-0.911***	-0.786***	-0.786***
	(0.0962)	(0.149)	(0.149)
Loaded	-0.370***	-0.248	-0.196
	(0.130)	(0.194)	(0.215)
Reveal×Loaded		-0.167	-0.167
		(0.205)	(0.205)
Market A	0.226***	0.224***	0.224***
	(0.0760)	(0.0762)	(0.0762)
Market B	-0.210***	-0.212***	-0.212***
	(0.0504)	(0.0507)	(0.0507)
Period	0.0647***	0.0651***	0.0781**
	(0.0177)	(0.0180)	(0.0373)
Period×Loaded			-0.0179
			(0.0425)
Constant	1.606***	1.513***	1.475***
	(0.128)	(0.159)	(0.182)
Observations	3,060	3,060	3,060
Pseudo R^2	0.145	0.145	0.145

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.4: Probit regression results on the equilibrium consistency of choices.

significant negative influence on the likelihood of subjects choosing the equilibrium action. This influence can also be shown using non-parametric tests. In the Loaded treatment, workers conceal when the equilibrium calls for revelation in 16%, 38%, and 33% of all decisions in Markets A, B and C, respectively; the corresponding frequencies for workers who reveal when the equilibrium predicts concealment are only 6%, 10%, and 6%. This difference is highly significant for all three markets (two-sided Wilcoxon signed-rank test, $p < 0.001$). In Neutral these figures read 11%, 26%, and 16% (if the prediction is to reveal) and 3%, 0%, and 5% (for workers with a prediction to conceal) and the difference is also significant (two-sided Wilcoxon signed-rank test, $p = 0.003$).

Observation 2. *In both* Loaded *and* Neutral*, workers who reveal in equilibrium violate the prediction significantly more often than workers who conceal in equilibrium.*

We further break down the behavior for the different productivities. Table 3.5 summarizes the equilibrium prediction and actual play for all six workers separately in the three markets. Consider workers who are expected to reveal in

Worker	1	2	3	4	5	6
			Market A			
Equilibrium	0	0	0	0	0	1
LOADED	0.02	0.07	0.04	0.06	0.10	0.84
NEUTRAL	0.04	0.02	0.02	0.02	0.07	0.89
			Market B			
Equilibrium	0	1	1	1	1	1
LOADED	0.10	0.32	0.44	0.65	0.81	0.85
NEUTRAL	0	0.35	0.71	0.78	0.91	0.96
			Market C			
Equilibrium	0	0	0	1	1	1
LOADED	0.04	0.03	0.09	0.41	0.77	0.83
NEUTRAL	0.04	0.04	0.09	0.62	0.93	0.98

Table 3.5: Average revelation rates across markets and treatments. An entry of 0 denotes that the worker is predicted to conceal while 1 denotes that the worker is predicted to reveal.

equilibrium, denoted by the entry of 1 in the "Equilibrium" row. Here, the differences between actual revelation rates and predictions are major, ranging from 15% up to 68% in LOADED. The table shows that these inconsistencies with equilibrium play are positively correlated with worker productivity for those workers who should reveal in equilibrium.[10] In contrast, inconsistencies with equilibrium play are not correlated with productivity when workers should conceal in equilibrium, and they are also generally small.[11] In NEUTRAL, the under-revelation result is less pronounced. But the same correlation for out-of-equilibrium conceal decisions can be found as well as no correlation for out-of-equilibrium reveal decisions.

Observation 3. *In both* LOADED *and* NEUTRAL, *choices inconsistent with the equilibrium prediction are correlated with productivity when workers should reveal but not when they should conceal.*

From Table 3.5 it can be taken that the discrepancy of revelation rates and predictions is positively correlated with the equilibrium share of reveal decisions. In Market A, only one in six workers is predicted to reveal and only minor discrepancies to the prediction occur. In Market B, it is the other way round: five in six workers are predicted to reveal and major discrepancies to the prediction occur. This is due to the observed tendency of under-revelation.

[10] A sign test (two-sided) on the sign of Spearman's ρ calculated for each group yields $p \leq 0.001$ for both, LOADED and NEUTRAL.

[11] A sign test (two-sided) on the sign of Spearman's ρ calculated for each group yields $p = 0.455$ for LOADED and $p = 0.508$ for NEUTRAL.

3.5.2 Framing Effect

As is apparent from the results reported above, subjects in the Neutral treatment reveal more often than in Loaded. We observe differences in three dimensions:

– When averaging across workers (Table 3.3), revelation rates are higher in Neutral than in Loaded for Markets B and C, although this is only significant in Market C (two-sided Mann-Whitney U-Tests, Market C: $p = 0.008$; Market B: $p = 0.132$).

– We find that more decisions are in line with the equilibrium prediction in Neutral than with the loaded frame. In Loaded, 79.8% of the decisions are consistent compared to 87.8% in Neutral. This difference is significant (two-sided Mann-Whitney U-Test, $p = 0.027$).

– The higher level of equilibrium play in Neutral has a distinct pattern: there are more equilibrium revelation choices, but not more equilibrium conceal decisions in Neutral compared to Loaded. Averaging across the three markets in Loaded, we observe 34.2% conceal decisions of workers who should reveal in equilibrium and 6.2% reveal decisions for workers who should conceal in equilibrium. For Neutral, the corresponding numbers are 20.8% and 3.6%. The decrease from 34.2% to 20.8% is significant (two-sided Mann-Whitney U-Test, $p = 0.024$). but the decrease from 6.2% to 3.6% is not (two-sided Mann-Whitney U-Test, $p = 0.356$).

The regression analysis in Table 3.4 supports these findings. *Loaded* leads to fewer equilibrium choices than the baseline treatment Neutral, as expected. Adding the interaction *Reveal*×*Loaded* suggests that decisions in Loaded are less likely to be consistent with the equilibrium only when they concern reveal decisions, as argued above: in regressions (2) and (3) of in Table 3.4, *Loaded* is insignificant but *Loaded* together with the interaction term *Reveal*×*Loaded* is significant at the 5% level (Wald tests, in regression (2) $p = 0.012$, and $p = 0.022$ in (3)).

Observation 4. *In* Neutral*, subjects reveal their productivity more often than in* Loaded*. While there are significantly more choices consistent with equilibrium in* Neutral*, this effect is quantitatively and statistically significant only for workers who should reveal in equilibrium.*

These findings suggest that the labor market frame in combination with the health certificate affects choices. It gives rise to preferences not restricted to the monetary incentives of the game. A share of subjects were more reluctant to disclose their productivity in the loaded treatment where private information concerned the subject's health status. Hence, revelation of private information increases or decreases depending on the contextual frame, without any real privacy issues at stake in the experiment.

3.5.3 Learning and Feedback

We now check whether subjects learn to play the equilibrium over time and whether or not a more detailed feedback accelerates learning. As mentioned, we have employed two different feedback formats in the treatment LOADED, namely LOADED_BASE and LOADED_FEED. In LOADED_BASE subjects were only informed about their own profits and about the market wage of that period. In LOADED_FEED subjects received additional information about the revelation decisions of all six workers in the group.

Figure 3.1 shows the frequency of choices consistent with equilibrium over time. We aggregate across markets because the time trends are virtually identical. There is an increase in equilibrium decisions in all three treatments, LOADED_BASE, LOADED_FEED and NEUTRAL. In NEUTRAL, the percentage of choices consistent with equilibrium is above 90% toward the end. The regressions in Table 3.4 confirm that these effects are significant. Learning does not vary across treatments as the interaction term between *Period* and *Loaded* in regression (3) is insignificant. A test for joint significance between *Period* and this interaction is also insignificant ($p = 0.429$). Hence, we infer that there are no differences concerning learning between *Loaded* and in *Neutral*.

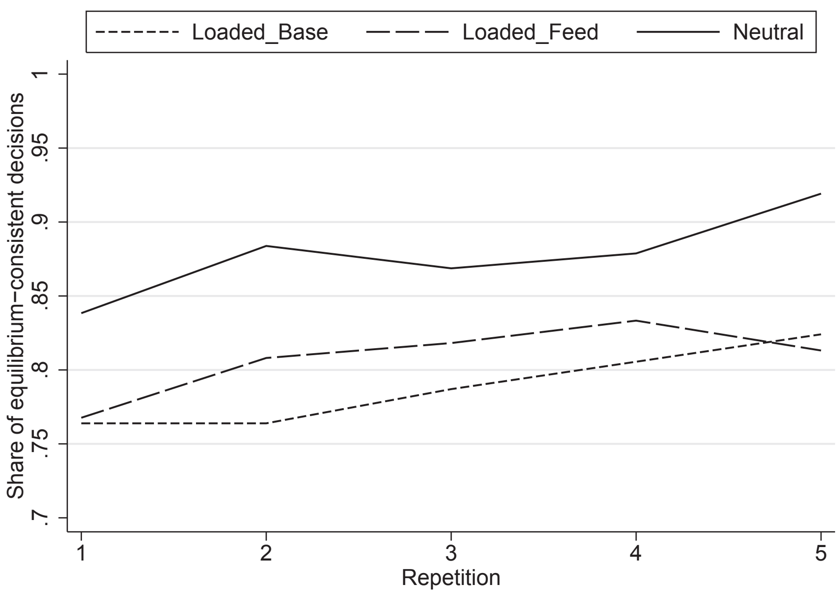


Figure 3.1: Fraction of equilibrium-consistent decisions across treatments over time.

The results from the variants LOADED_BASE and LOADED_FEED are very similar. Regarding the consistency of choices with the equilibrium predictions, we find that 78.9% and 80.9% of the decisions are consistent in LOADED_BASE and LOADED_FEED, respectively. The difference is not statistically significant

($p = 0.558$). The measures for under- and over-revelation with respect to the equilibrium predictions are also hardly distinguishable. About one-third of the decisions, 35.3% in LOADED_BASE and 32.9% in LOADED_FEED, are classified as under-revelation while the numbers for over-revelation are 6.9% and 5.5% in LOADED_BASE and LOADED_FEED, respectively. Neither under- nor over-revelation varies significantly across these two treatments, with corresponding p-values of 0.758 and 0.685. We also compared decisions between the two different feedback formats per market and per period but did not find any significant differences.

The findings in this section suggest that learning is sluggish in the revelation game. From this we take that the observed unraveling but also the under-revelation are robust phenomena that cannot easily be influenced by repeated play of similar games. Of course, further repetitions might lead to a higher consistency with equilibrium. However, in many of the examples mentioned in the introduction, players have only few opportunities to learn.

3.6 Behavioral forces against revelation

Despite a relatively large congruence with the predictions at the market level (Observation 1), we trust it is worthwhile to further investigate Observations 2 and 3 which suggest that there is a tendency to under-reveal. We consider (i) level-k reasoning, (ii) quantal response equilibrium, and (iii) inequality aversion. Whereas the analysis is *not* aimed at conducting a horse race among behavioral models, we believe that level-k or a limited depth of reasoning is a prime and parsimonious model for explaining our data. Accordingly, we focus on the level-k model here and relegate quantal response equilibrium and inequality aversion to the appendix. As none of the models can explain the observed framing effect, we focus on the treatment NEUTRAL while keeping in mind that in LOADED the under-revelation is even more pronounced.

To apply level-k reasoning to the revelation game, we assume that level-0 players randomize with probability 0.5 between their two actions, although the exact level-0 assumption does not matter much qualitatively for our game.[12] We then calculate the best replies for $k > 1$ where level-k' players (for $k' > 0$) believe that all other players reason at level $k = k' - 1$.

Table 3.6 displays the required levels of reasoning for players to pick their equilibrium action in the various markets for different productivities. The fewest

[12] A different yet plausible assumption for level-0 types is that all workers conceal with probability one. In that case, it is straightforward to check that Markets A and B remain as in Table 3.6, but, in Market C, also worker 5 reveals when $k = 1$ and worker 4 when $k = 2$. Less plausible, in our view, is the level-0 assumption that all workers reveal with probability one. If so, the prediction is the same as in the case where all workers conceal with probability one with all k-levels augmented by one. The logic is that when all players reveal, the $k = 1$ reply for all workers is to conceal with probability one.

iterations are required in Market A. The highest level-k requirement occurs in Market B for player 2 who has to perform five steps of reasoning. We note that level-k reasoning yields Nash equilibrium choices for a finite number of steps.

Importantly, Table 3.6 also shows that taking the (equilibrium) decision to conceal merely requires a level of 1 throughout. By contrast, revealing requires up to $k = n - 1$ levels. As this property is central to our research question, we prove this generally.

Productivity	Market A	Market B	Market C
θ_1	$200^{k\geq1}$	$200^{k\geq1}$	$200^{k\geq1}$
θ_2	$210^{k\geq1}$	$\mathbf{448}^{k\geq5}$	$280^{k\geq1}$
θ_3	$230^{k\geq1}$	$\mathbf{510}^{k\geq4}$	$360^{k\geq1}$
θ_4	$260^{k\geq1}$	$\mathbf{551}^{k\geq3}$	$\mathbf{440}^{k\geq3}$
θ_5	$300^{k\geq1}$	$\mathbf{582}^{k\geq2}$	$\mathbf{520}^{k\geq2}$
θ_6	$\mathbf{600}^{k\geq1}$	$\mathbf{607}^{k\geq1}$	$\mathbf{600}^{k\geq1}$

Table 3.6: Minimum k-level required for a player to choose her equilibrium action. Productivities in bold face indicate that this worker reveals in equilibrium.

Proposition 3. *In the revelation game, workers who conceal if they are level $k > 1$ also conceal if they are level-*1.

The proof can be found in the appendix. The proposition suggests that concealing already occurs for the lowest level of reasoning ($k = 1$): it is not possible, for example, that a worker reveals when she is a level-1 type but conceals when she is level 2.

The level-k patterns in Table 3.6 offer an explanation of Observations 2 and 3. As seen in Proposition 3, the revelation game requires increasingly higher levels of reasoning for the equilibrium decision to reveal, but only level-1 reasoning for equilibrium decisions to conceal. Under the assumption that at least some players display limited depth of reasoning, this implies (i) disproportionally more concealment in general, (ii) more consistency with the equilibrium prediction for workers who conceal than for those who reveal in equilibrium, and (iii) a negative correlation of equilibrium revelation decisions with productivities which does not hold for equilibrium conceal decisions.

More specifically, the level-k model predicts that the frequency of conceal decisions should be equal to the frequency of reveal decisions by worker 6 in all three markets because all of these decisions require at least level-1 reasoning. We find support for this hypothesis as we observe no significant differences in the fraction of equilibrium choices by those players (two-sided Wilcoxon matched pairs test, $p = 0.153$).[13]

[13] In LOADED, there is more under-revelation by worker 6 than over-revelation by those

Consistency	(4)	(5)	(6)
Min_k	-0.498***	-0.459***	-0.470***
	(0.0326)	(0.0339)	(0.0692)
Reveal		-0.443***	-0.444***
		(0.106)	(0.105)
Loaded		-0.421***	-0.457*
		(0.148)	(0.251)
Market A		0.0667	0.0670
		(0.0795)	(0.0799)
Market B		0.249***	0.249***
		(0.0564)	(0.0571)
Period		0.0744***	0.0744***
		(0.0200)	(0.0200)
Loaded×Min_k			0.0155
			(0.0780)
Constant	1.932***	2.102***	2.129***
	(0.0977)	(0.161)	(0.227)
Observations	3,060	3,060	3,060
Pseudo R^2	0.197	0.228	0.228

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.7: Probit regression results on the equilibrium *consistency* of choices.

The relevance of level-k reasoning can also be taken from the regression analysis summarized in Table 3.7 (the data are again clustered at the group level). In these regressions we consider the cardinal variable *Min_k*, defined as the minimum k-level required for an individual worker to choose her equilibrium action. This variable is highly significant in all regressions. That higher requirements on subjects' reasoning lower the likelihood for equilibrium play appears to have strong explanatory power. From column (5) it can be taken that adding the variables of the regressions in Table 3.4 hardly affects the coefficient of the minimum k-level required. In addition, we find that the variable *Min_k* fully explains the difference between the baseline Market C and Market A. The dummy variable *Market B* now has a positive influence on equilibrium play relative to Market C. Hence, the different behavior observed in the three markets is mainly a result of the different cognitive challenges of these markets.

The level-k model delivers an intuitive explanation for the behavioral patterns we observe in the experiments. As low-productivity workers with a prediction to

workers who conceal in equilibrium. This can be attributed to the framing effect causing lower revelation rates.

reveal need to anticipate other workers' behavior much more accurately, their decisions are more challenging compared to high-productivity workers who should conceal. It follows that these low-productivity workers are more prone to making decisions that are inconsistent with the equilibrium and, consequently, there should be more under-revelation than over-revelation.

Concluding this section, we briefly discuss Quantal Response Equilibrium (QRE), developed by McKelvey and Palfrey (1995), and inequality aversion as further candidates for the analysis of deviations from standard Nash equilibrium. Detailed analyses can be found in the Appendix.

QRE is a generalization of Nash equilibrium that takes decision errors into account: workers do not always choose the best response with probability one but they choose better alternatives more frequently than others. Therefore, QRE allows for out-of-equilibrium choices to conceal and reveal one's productivity. The distribution we estimate fits quantitatively well with the data. Having said that, QRE predicts substantial rates of both out-of-equilibrium revelation and conceal decisions. In the data out-of-equilibrium revelation occurs only rarely—a finding that is captured well by the level-k model but not by QRE.

Inequality aversion proposed by, among others, Fehr and Schmidt (1999) suggests that players are concerned not only about their own material payoff but also about the difference between their own payoff and other players' payoffs. Overall, inequality aversion is consistent with our results. There are equilibria with inequality averse subjects where fewer players reveal than in the standard Nash equilibrium, and we find no equilibria where more players reveal than in the Nash equilibrium. Having said that, there are some limits of inequality aversion for rationalizing our data. Firstly, and perhaps surprisingly, the standard Nash equilibrium is very often also an equilibrium with inequality averse players. Secondly, coordination problems may occur due to multiple equilibria. Thirdly, the equilibria broadly consistent with our results occur only very rarely in the calibrated simulations we employ.

3.7 Conclusion

We study experimental labor markets where workers have private information about their productivity which they can perfectly reveal at a cost. The equilibrium entails unraveling and the disclosure of private information. Depending on the market parameters, unraveling can be predicted to be only partial.

The data indicate that participants often reveal their productivity, consistent with equilibrium play. The theory also predicts the differences between markets well. Having said that, workers tend to reveal less often than predicted in our experiments. Specifically, the propensity to conceal when the equilibrium calls for revelation is in stark contrast to the low frequency of decisions inconsistent with equilibrium when a worker should conceal. These findings are robust across both treatments we conducted.

Three behavioral models suggest the incomplete unraveling we observe: level-k reasoning, quantal-response equilibrium, and inequality aversion, although for different reasons. Level-k reasoning and quantal-response equilibrium predict that boundedly rational players will conceal frequently, and only with fully rational players will there be complete unraveling. Out-of-equilibrium revelation, by contrast, will be rare as concealing in equilibrium does not require more than one step of reasoning (level-1 type). Inequality-averse players may be reluctant to reveal when it increases payoff differences.

With the help of a treatment using a neutral frame we also identify a framing effect. When the wording suggests that the information to be disclosed is particularly sensitive, subjects reveal significantly less frequently compared to the neutral frame. We believe that this framing effect is driven by the subjects' privacy concerns, and that subjects have a taste for privacy *per se*.

Even though we do not observe complete unraveling and even though we are able to identify behavioral forces against revelation, we do not believe that our results suggest that voluntary revelation is unimportant in the privacy debate. The substantial revelation rates we observes (roughly forty percent where fifty percent are predicted) are even more worrisome since incentives for revelation in the field may be even stronger. For example, decision making may be sequential (rather than simultaneous) in the field. If so, complete unraveling will occur even for myopic players. Also, the repeated interaction within groups we employ which makes the externality transparent and obvious may be a further difference to the field that facilitates unraveling. Third, players whose productivity is earned by merit (rather than being random) might feel entitled to a higher payoff and thus more inclined to reveal. Unraveling is likely to occur *a fortiori* in such field settings. We therefore believe that the debate about how to limit the externalities of voluntary disclosure and how to regulate information disclosure is highly relevant.

3.A Further behavioral models

Quantal Response Equilibrium

The Quantal Response Equilibrium (QRE), developed by McKelvey and Palfrey (1995), is a generalization of Nash equilibrium that takes decision errors into account: workers do not always choose the best response with probability one but they choose better alternatives more frequently than others. Therefore, QRE allows for out-of-equilibrium choices to conceal and reveal one's productivity.

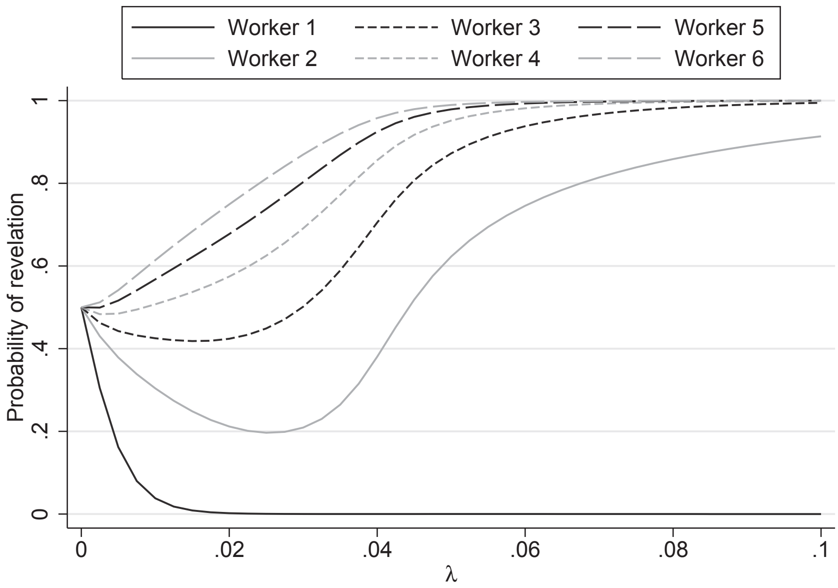


Figure 3.2: QRE predictions for Market B.

We employ the logit equilibrium variant of QRE. Worker i believes that the other workers will choose to reveal with certain belief probabilities and calculates her expected payoff from concealing based on this belief (the payoff from revealing is simply the productivity minus the revelation cost). Workers make better choices more frequently. In particular, choice probabilities are specified to be ratios of exponential functions where expected payoffs are multiplied with λ, the rationality parameter. This parameter captures deviations from the Nash equilibrium: if $\lambda = 0$, behavior is completely noisy and both choices are equally likely regardless of their expected payoff; as $\lambda \to \infty$, workers choose the best response with probability one. In the logit equilibrium, beliefs and choice probabilities are consistent.

As an example, Figure 3.2 displays the QRE predictions (revelation frequencies given the rationality parameter λ) for Market B. We note that QRE can explain the under-revelation result: for any $\lambda > 0$, the error probabilities are higher for workers 2 to 6 who reveal in equilibrium than for worker 1, suggesting too little revelation. The relationship between the probability of revealing and λ is even non-monotonic for some workers, so a higher λ can be associated with less revelation. The intuition is that the likelihood that worker 6 reveals must meet a certain threshold before other workers start preferring revelation over concealment. Thus, λ must be high enough. On the other hand, the higher the parameter λ, the more weight the best response gets such that the propensity to conceal can increase in λ as long as worker 6 does not reveal with a significantly high probability. Such a non-monotonicity cannot be observed for workers that should conceal in equilibrium in any of our markets. Qualitatively, Market C looks the same as Figure 3.2. In Market A, there are no non-monotonicities since all workers except worker 1 conceal in equilibrium.

We conduct a maximum-likelihood estimation of the QRE parameter λ for the treatment NEUTRAL. Following Haile, Hortaçsu, and Kosenok (2008), the estimation is implemented jointly for our three markets such that there is only one free parameter in the model we estimate. We find an estimate of $\lambda = 0.035$ with a standard error of 0.0015, suggesting that λ significantly differs from zero.[14]

Worker	1	2	3	4	5	6
			Market A			
Nash	0	0	0	0	0	1
QRE	<0.01	0.01	0.02	0.06	0.20	>0.99
NEUTRAL data	0.04	0.02	0.02	0.02	0.07	0.89
			Market B			
Nash	0	1	1	1	1	1
QRE	<0.01	0.27	0.60	0.78	0.87	0.92
NEUTRAL data	0.00	0.35	0.71	0.78	0.91	0.96
			Market C			
Nash	0	0	0	1	1	1
QRE	<0.01	0.02	0.21	0.67	0.93	0.99
NEUTRAL data	0.04	0.04	0.09	0.62	0.93	0.98

Table 3.8: QRE estimates and data from NEUTRAL

Table 3.8 summarizes the QRE prediction for the λ we estimated from the data and contrasts this prediction with our findings. Overall, QRE fits the data well. It correctly predicts the degree of under-revelation (of workers 2, 3, 4, 5, and 6 in Market B; and workers 4, 5, and 6 in Market C). The predicted and observed frequencies of revelation are remarkably similar. Also, the low revelation frequencies of low-productivity workers who should conceal in equilibrium are predicted rather well (workers 1, 2, and 3 in Market A; and workers 1 and 2 in Market C). On the other hand, the QRE predictions for some of the workers who

14 Separate estimates for the three markets yield $\lambda_A = 0.026$, $\lambda_B = 0.039$ and $\lambda_C = 0.029$. The QRE estimate for the three markets in LOADED is $\lambda = 0.017$

conceal in equilibrium do not perform as well. QRE predicts substantial rates of out-of-equilibrium revelation decisions with about 20% for worker 5 in Market A and for worker 3 in Market C. In both cases, less than 10% revelation is observed. Nevertheless, the QRE model captures the overall patterns of behavior well and can therefore account for the lower revelation rates that we observed compared to the equilibrium.

Inequality aversion

Does fairness prevent the full revelation of private information? In our game, when the highest productivity worker chooses to reveal it increases her own payoff but imposes a negative externality on others.[15] Similarly, given the best worker reveals, the same can hold true for the second most productive worker. Accordingly, inequality-averse subjects may be less inclined to reveal their productivity than the standard model of selfish payoff maximizers suggests. While such motives may play only a minor role in large markets like the labor market, they may be important in smaller groups (small teams or enterprises) and in our experimental groups of six.

We use the model of inequality aversion proposed by Fehr and Schmidt (1999) (henceforth F&S) where players are concerned not only about their own material payoff but also about the difference between their own payoff and other players' payoffs. As a consequence the players' utility is

$$U_i(x_i, x_j) = x_i - \frac{\alpha_i}{n-1}\sum_{j\neq i}\max[x_j - x_i, 0] - \frac{\beta_i}{n-1}\sum_{j\neq i}\max[x_i - x_j, 0]$$

where, x_i and x_j denote the monetary payoffs to players i and j, and α_i and β_i denote i's aversion toward disadvantageous inequality (envy) and advantageous inequality (greed), respectively. Standard preferences occur for $\alpha = \beta = 0$. Following F&S, we assume $0 \leq \beta_i < 1$.

There are two complications regarding the impact of inequality aversion. One issue is that the effect on inequality of (not) revealing one's productivity will often be ambiguous: a worker may find that concealing reduces the advantageous inequality with respect to less productive workers but it may also increase the payoff difference to the more productive workers provided they reveal. So this worker may stick with her (standard) equilibrium action even if she is inequality averse. Another complication is that there are multiple equilibria. It is not straightforward to show which of the $2^6 = 64$ possible outcomes can be an equilibrium for inequality-averse players and which cannot.

15 As an example, consider Market A. The Nash equilibrium has only worker 6 revealing her productivity, and worker 6 earns 500 points in equilibrium whereas all others earn 240 points. If worker 6 did not reveal, everybody would earn 300 points. It follows that, for a sufficiently inequality-averse subject, concealing may yield a higher utility than revealing.

To tackle these issues we employ simulations based on a calibrated version of the model to identify the F&S equilibria of the revelation game. The model is calibrated using the joint distribution of the α and β parameters observed in Blanco, Engelmann, and Normann (2011). For each subject, they derive an α_i from rejection behavior in the ultimatum game and a β_i from a modified dictator game. There are 61 subjects in this data set with 58 different α_i-β_i types.[16] Note that we need the *joint* distribution of the parameters, which is unavailable elsewhere. The computer simulations are implemented as follows: In each trial, the program randomly assigns an α_i-β_i parameter combination to each of the six workers (with replacement), where the 61 α_i-β_i types in the Blanco et al. (2011) data were equally likely. Given the realization of inequality parameters, the program then systematically checks which of the 64 possible outcomes turns out to be an equilibrium. Note that there can be multiple equilibria, which is also the reason why the percentages do not add up to 100%. For the three markets A, B, and C separately, we ran 100,000 trials.

	Actions of workers							Market	
No.	I_1	I_2	I_3	I_4	I_5	I_6	A	B	C
1	0	1	1	1	1	1	–	90.5%	–
2	0	0	1	1	1	1	–	3.9%	–
3	0	0	0	1	1	1	–	7.2%	61.9%
4	0	0	0	0	1	1	–	9.5%	20.2%
5	0	0	0	0	0	1	80.3%	14.8%	17.0%
6	0	0	0	0	0	0	19.7%	55.6%	8.4%
7	0	0	0	0	1	0	–	–	5.2%

Table 3.9: Summary of F&S equilibria. Note: because of multiple equilibria, the figures do not always add up to one hundred percent.

The simulation results are summarized in Table 3.9 which can be read as follows. First, note that seven equilibria emerge out of the 64 possible outcomes where each is described in a separate row of the table. In equilibrium 1, only worker 1 chooses to conceal while all the other workers reveal. This strategy profile was an F&S equilibrium in 90.5% of the 100,000 simulations of Market B where it is also the standard Nash equilibrium. There appear to be no F&S parameters which support this outcome as an equilibrium for Market A or C.

Overall, inequality aversion is consistent with our results. The simulations show that there are equilibria with F&S preferences where fewer players reveal than in a standard Nash equilibrium, and there are no F&S equilibria where more players reveal than in a Nash equilibrium.

[16] There are no significant differences between the distributions of α that Blanco et al. (2011) elicit and the one assumed in Fehr and Schmidt (1999). The distributions of β differ, but they are still roughly comparable.

Having said that, there are some aspects of the simulations that show the limits of inequality aversion for rationalizing our data. Firstly, and perhaps surprisingly, the standard Nash equilibrium is very often also an equilibrium with F&S preferences. In all three markets, it is the most frequent equilibrium: 90.5% (Market B), 80.3% (Market A) and 61.9% (Market C) of the 100,000 random realizations of α_i-β_i parameter combinations. Relatedly, the F&S equilibria consistent with our data occur with rather low frequencies. In other words, there are only a few F&S parameter combinations that support these equilibria. For instance, in Market B, we observe especially little revelation by workers 2 and 3 which may be captured by the F&S equilibria numbered 2 and 3. However, these equilibria do not occur often in the simulations. Moreover, the calibrated F&S model predicts that there is an equilibrium in which no worker reveals (equilibrium 6), and this equilibrium occurs in more than 50% of the runs for Market B where we in fact observe a lot of revelation, in line with the equilibrium prediction.

Secondly, the simulations show that coordination problems may occur due to multiple equilibria. In Market B there is a unique equilibrium in 26.6% of the cases, two equilibria in 65.5%, and three equilibria in 7.9% of the cases. The corresponding values for Market C are 87.3% and 12.7% for one or two equilibria, respectively. It is unclear how inequality-averse players can resolve the coordination problems resulting from multiple equilibria. In Market A, we always found a unique equilibrium, but this market is not strongly supportive of inequality aversion either. The equilibrium for Market A can be found analytically: worker 6 will not reveal if and only if $\beta_i > 200/260 \approx 0.8$. This condition will be met for 20% in the data set of Blanco et al. (2011) (and our simulations indicate exactly the same frequency for the occurrence of this equilibrium). In Neutral this equilibrium occurs, however, only with a frequency of 11%. While the loaded frame leads to results closer to the prediction, inequality aversion should not be driven by the frame. Overall, we can explain the observed outcomes as equilibria when players have F&S preferences.

Discussion

Our goal has been to investigate how behavioral models might suggest behavioral forces affect revelation. The three canonical behavioral models discussed all suggest that players might be biased not to reveal. By contrast, we found hardly any support for a hypothesis suggesting that players reveal too much as compared to the equilibrium.

We believe that level-k rationality or a limited depth of reasoning is a prime model for explaining our data. Level-k implies that equilibrium concealment only requires $k = 1$ whereas revelation may require higher levels of reasoning. When higher levels of reasoning are increasingly rare among subjects, it follows for our setup that there is generally too little revelation; the lower the worker's productivity, the less likely the worker will reveal if the equilibrium calls for revelation; and there are virtually no equilibrium-inconsistent reveal decisions. This is what we see in the data.

In different manners level-k and QRE take into account that the payoff from concealing will *ceteris paribus* become more attractive than the payoff from revealing, $\theta_i - c$, for workers with low θ. It requires a "high level of rationality" (high k or high λ) for unraveling to occur to the extent predicted in equilibrium. Thus, both models suggest that the unraveling process might be stuck after a few players, leading to less revelation.

Markets played by fully rational yet inequality-averse players may also unravel only incompletely. The negative externality imposed on others may make even high-productivity workers conceal. On the other hand, inequality aversion supports the Nash equilibrium with standard preferences. Another difficulty is that multiple equilibria occur, which reduces the predictive power of such preferences.

3.B Proofs

Proof of Proposition 1.

Proof. We first show that $I_1^* = 0$. By concealing, the lowest productivity-worker earns at least θ_1 (namely when all other workers reveal, otherwise more), but worker 1 earns $\theta_1 - c < \theta_1$ by revealing. Hence, concealing is strictly dominant for worker 1 and we have $I_1^* = 0$ in equilibrium.

Next, we prove that $I_i^* = 0 \wedge I_j^* = 1$ only if $\theta_i < \theta_j$ strictly. Consider an equilibrium outcome with $I_i^* = 0$ and $I_j^* = 1$ and denote $\theta' = \sum_{m \neq i,j}(1 - I_m)\theta_m$ and $I' = \sum_{m \neq i,j}(1 - I_m)$. Now $I_i^* = 0$ and $I_j^* = 1$ are best replies to action profile I' if and only if

$$\theta_i - c \leq \frac{\theta_i + \theta'}{1 + I'} \tag{3.1}$$

$$\theta_j - c \geq \frac{\theta_i + \theta_j + \theta'}{2 + I'} \tag{3.2}$$

where the inequality for player i follows from $I_i = 0$ and the inequality for j follows from $I_j = 1$. Solving both equations for θ', we obtain

$$-c + (\theta_i - c)I' \leq \theta' \leq \theta_j - \theta_i - 2c + (\theta_j - c)I' \tag{3.3}$$

and

$$0 \leq -c + (\theta_j - \theta_i)(1 + I') \tag{3.4}$$

which holds only if $\theta_i < \theta_j$ strictly. Since $I_i^* = 0 < 1 = I_j^*$ only if $\theta_i < \theta_j$, we cannot have $I_{i+1}^* < I_i^*$ and thus $I_n^* \geq I_{n-1}^* \geq ...I_2^* \geq I_1^*$ as claimed. □

Proof of Proposition 2.

Proof. We first show that, if $\min(R) > \max(C)$ as asserted in the proposition, we get a unique equilibrium. Assume that, say, $R = \{n, n-1, ..., m\}$ and $C = \{m-1, m-2, ..., 1\}$. Then the pure strategy action profile

$$1 = I_n^* = I_{n-1}^* = ... = I_m^* > I_{m-1}^* = ... = I_2^* = I_1^* = 0$$

is a Nash equilibrium by the definition of R and C.

Now consider another pure strategy equilibrium candidate where, from Proposition 1, we only need to consider outcomes where $I_n^* \geq I_{n-1}^* \geq ... \geq I_2^* \geq I_1^* = 0$. Assume first that more workers reveal in this equilibrium candidate than in the first equilibrium, that is, workers $m-1$ to $m-k$, $k \geq 1$, reveal in this alleged equilibrium (whereas they conceal in the first equilibrium):

$$1 = I_n^* = I_{n-1}^* = ... = I_m^* = I_{m-1}^* = ... = I_{m-k}^* > I_{m-k-1}^* = ... = I_2^* = I_1^* = 0$$

For this to be a Nash equilibrium, we necessarily need $\theta_{m-k} - c \geq \frac{1}{m-k}\sum_{j=1}^{m-k}\theta_j$. However, this requires that $m-k \in R$ which is a violation of $\min(R) > \max(C)$. Consider a different pure strategy equilibrium candidate and where fewer workers reveal; say, workers m to $m+k$, $k \geq 0$ conceal (whereas they reveal in the first equilibrium). Here, we necessarily need $\theta_{m+k} - c \leq \frac{1}{m+k}\sum_{j=1}^{m+k}\theta_j$ for this outcome to be a Nash equilibrium. Hence, $m+k \in C$ which violates the assumption in the proposition. Hence, if $\min(R) > \max(C)$, the first Nash equilibrium is the unique pure-strategy equilibrium.

We now show the "only if" part of the proposition by proving that, if $\min(R) > \max(C)$ is violated, we get multiple equilibria. Let m be the highest worker in C and l be the lowest worker in R and assume the violation: $m > l$. First, note that $m \in C$ iff $\theta_m - c \leq \bar{\theta}(m)$ which, implies that concealment is a best-response for the workers $1, ..., m$ given that the remaining workers reveal. From $m = \max(C)$ it follows that $\theta_{m+1} - c > \frac{\theta_{m+1}+\sum_{j=1}^{m}\theta_j}{m+1}$ and, by the definition of m, the inequality will also hold for all workers $m+1, ..., n$. Hence, we have a Nash equilibrium where the workers $1, ..., m$ conceal and the workers $m+1, ..., n$ reveal. Second, note that $l = \min(R)$ implies $\theta_{l-1} - c < \frac{\theta_{l-1}+\sum_{j=1}^{m-2}\theta_j}{l-1}$, that is, concealment is a best-response for the workers $1, ..., l-1$ given that the remaining workers reveal. As for the remaining workers, $l \in R$ implies $\theta_l - c \geq \frac{\theta_l+\sum_{j=1}^{l-1}\theta_j}{l}$ and the same inequality will hold for all workers $l, ..., n$. Hence we have a second Nash equilibrium where the workers $1, ..., l-1$ conceal and the workers $l, ..., n$ reveal. Hence, if $\min(R) > \max(C)$ is violated, multiple equilibria occur and the proposition follows. □

Proof of Proposition 3.

Proof. We prove the proposition by establishing a contradiction: suppose some worker conceals for $k = 2$ but reveals for $k = 1$. This yields a contradiction because, as we will show, the expected payoff from concealing is higher if $k = 1$ than if $k = 2$.

We first derive the best reply of a $k = 1$ player. Player i (when $k = 1$) believes that all other players randomize across both actions with a probability of 0.50. To calculate the payoff from concealing, player i needs to take into account all possible contingencies that may arise (no other player concealing, one of the $n - 1$ other players concealing and so on) which yields a complex combinatoric expression. Specifically, player i (when $k = 1$) will reveal if and only if

$$\theta_i - c \geq \frac{\theta_i \sum_{a=0}^{n-1} \frac{\binom{n-1}{a}}{a+1} + (\sum_{j \neq i} \theta_j)(\sum_{a=1}^{n-1} \frac{\binom{n-2}{a-1}}{a+1})}{2^{n-1}} \tag{3.5}$$

or

$$\theta_i - c \geq \frac{\theta_i \sum_{a=0}^{n-2} \frac{\binom{n-2}{a}}{a+1} + (\sum_{j \in I} \theta_j)(\sum_{a=1}^{n-1} \frac{\binom{n-2}{a-1}}{a+1})}{2^{n-1}} \tag{3.6}$$

where the numerator arises because all possibilities occur with equal probability.

Note that, if (3.6) is met for player i, it will also be met for all workers with $\theta_j \geq \theta_i$. This follows from the observation that the factor of θ_i on the RHS of (3.6) is strictly smaller than one. Hence (when $k = 1$), workers $\theta_1, ..., \theta_m$ will conceal and workers $\theta_{m+1}, ..., \theta_n$ will reveal for some $m \geq 1$, unless we have the trivial case where all workers conceal.

As a next step, we show that a necessary condition for worker i to reveal (when $k = 1$) is $\theta_i > \frac{\sum_{j=1}^{n} \theta_j}{n}$. To prove this, we evaluate RHS of (3.6) when $\theta_i = \frac{1}{n} \sum_{j=1}^{n} \theta_j$. Simple but tedious combinatorics show a rather intuitive result, namely that this expression is greater or equal than the average worker productivity if and only if $\theta_i \geq \frac{1}{n} \sum_{j=1}^{n} \theta_j$. Thus, (3.6) will be met only if worker i's productivity is above average.

We now establish the fact that the condition for a $k = 2$ worker to conceal is weaker than the condition for a $k = 1$ worker to conceal. When $k = 2$, worker i believes that all other players are level $k = 1$, and, accordingly, that $\{\theta_1, \theta_2, ...\theta_m\}$ will conceal with probability one. Player i will conceal (when $k = 2$) if and only if:

$$\theta_i - c \leq \frac{\theta_i + \sum_{i=1}^{m} \theta_j}{m+1}. \tag{3.7}$$

Now, for worker i to reveal when $k = 1$ necessarily requires $\theta_i - c \geq \frac{1}{n} \sum_{j=1}^{n} \theta_j$ but to conceal when $k = 2$ requires (3.7). Putting these condition together, we obtain

$$\frac{\theta_i + \sum_{i=1}^{m} \theta_j}{m+1} \geq \theta_i - c > \frac{\sum_{i=1}^{n} \theta_j}{n}. \tag{3.8}$$

This, however, cannot hold: it is not possible that the average of the low-productivity workers $1, ..., m$ plus worker i is larger than the average productivity of all workers because $\theta_i > \sum_j \theta_j / n$ for all $i > m$.

Since the condition for revealing as a $k = 1$ player contradicts the condition for concealing as a $k = 2$ player, it cannot be that player i reveals as a level $k = 1$ but but conceals as level $k = 2$. Hence, if player i conceals for $k = 2$, she will do so with $k = 1$ steps of reasoning.

Finally and intuitively, similar arguments show that a worker will conceal if $k = 2$ if she conceals when $k = 3$ and so on for a higher k. With a higher k, high types will "drop out" by revealing, leading to even lower concealment wages. Hence, workers who conceal for some k' will not reveal when $k < k'$. $\square$

3.C Instructions (Treatment Loaded)

Welcome to this experiment on economic decision making.

Please read these instructions carefully. The experiment is conducted anonymously, that is, you will not get to know which of the other participants interacted with you or which participant acted in which role. Please note that now that the experiment has started, you must not talk to other participants. If you have any questions, please raise your hand and we will come to you.

In this experiment all participants act as workers. The workers in this experiment differ with respect to their state of health. The state of health of a worker determines his or her productivity and hence also the revenue of a fictional employer (played by the computer). Furthermore, there are in total three different labor markets, which are played on a rotating basis: labor market A, labor market B and labor market C. At the beginning of each period, you will see a screen showing which market is being played in that period. There are six different workers with different states of health.

	Labor Market A	Labor Market B	Labor Market C
Worker 1	200	200	200
Worker 2	210	448	280
Worker 3	230	510	360
Worker 4	260	551	440
Worker 5	300	582	520
Worker 6	600	607	600
Average	300	483	400

Table 1: State of health of the workers 1-6 in the three labor markets.

In the table above you can see the different workers of this experiment and their state of health. Suppose market B is being played in this period. If the fictional employer (who is played by the computer) is hiring, for example, worker 3, then worker 3 will create a revenue of 510 points for the employer. Worker 1 will create a revenue of 200 points due to worse health. In a period where market C is being played the workers 1 and 3 create revenues of 200 (worker 1) or 360 points (worker 3). The state of health of any worker is of course completely fictional and is determined randomly by the computer.

The experiment lasts for 15 periods. At the beginning of a period a random draw will determine whether you act in the role of worker 1, 2, 3, 4, 5, or 6, and you will also be informed about the labor market being played in that period. Each group consists of six workers of different states of health. There is exactly one worker 1, one worker 2, one worker 3, and so on, and one worker 6 in each group. All workers 1 and 6 occur exactly once in each group. As mentioned before you will be informed about the market being played (A, B or C) at the beginning of a period.

Your task in the experiment:

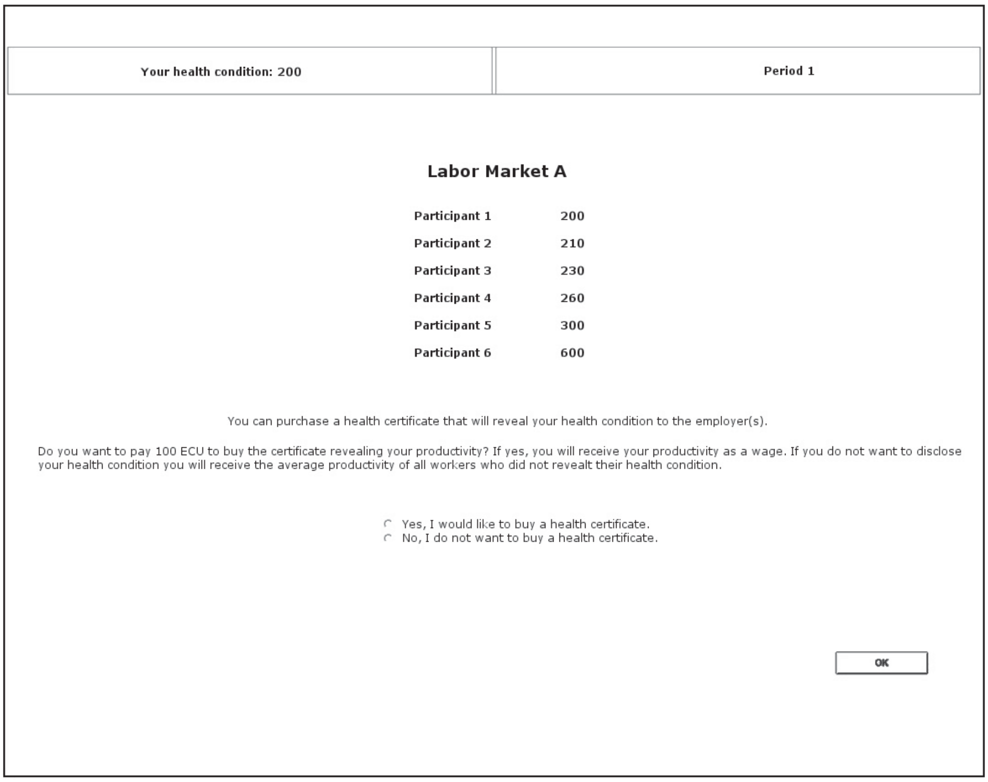
In each period all workers have to make the following decision. You choose whether or not to buy a health certificate at a cost of 100 points. The health certificate will reveal your state of health and will affect your payment in that period. Your payments depend on whether you purchased the health certificate:

1. If you choose to buy the health certificate you will receive your state of health in points as a wage payment minus the costs of 100 points.

2. If you do not purchase the health certificate your wage payment will be the average state of health of all participants who did not purchase the health certificate.

All workers decide simultaneously whether to purchase the health certificate. When you decide, you will not know how many (if any) of the other workers have chosen to buy the certificate. You will also not know the final market wage when making your decision. This information will be given only at the end of a period.

Once all workers have made their decisions you will receive detailed information on the period's results. The next period will begin as soon as all participants have read the summary and clicked on "Continue". Here is an example of the decision screen for market A and worker 1 with a state of health of 200:



Example: Suppose market B is being played this period. The average state of health of all employees is:

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

The market wage would equal 483 points in this case. Now each worker decides whether to reveal his or her state of health. Once all participants have made their choice everybody will receive detailed information on the results. The table above also lists the average state of health for the markets A and C.

Assume that the workers 3 and 5 have revealed their state of health. In this case worker 3 would receive a wage payment of 510 points and worker 5 a wage payment of 582 points. Both chose to reveal their state of health and as a consequence both have to pay the costs of 100 points. Worker 3 earns 510-100 = 410 points and worker 5 earns 482 points in that period. The other workers (1, 2, 4, and 6) do not have to pay the costs and will receive the market wage as a payment. In this example the average state of health of all workers who do not have a health certificate is: $\frac{200+448+551+607}{4} = \frac{1806}{4} = 451.5$ points. This is also the market wage for the workers 1, 2, 4 and 6. In the experiment you receive this information after you have made your decision.

As mentioned earlier, the experiment will last 15 periods in total. After the experiment your earnings will be converted at a rate of: 500 points = 1 Euro. Furthermore, we will round up your payoff to the next 50-cent amount. At the end of the experiment, please wait inside your cubicle until we call you to pick up your payment. Please return any documents you have received from us.

If you have any further questions please raise your hand now!

Chapter 4

Voluntary Disclosure of Private Information and Unraveling in the Market for Lemons: An Experiment

4.1 Introduction

Information asymmetries are fundamentally important for many markets. In the labor market, firms seek to hire outstanding employees, but in advance they cannot know for sure which candidates will turn out best. Insurance companies or banks need to minimize their risk exposure by selecting their customers appropriately. However, they cannot easily distinguish between clients they should do business with and clients they should avoid. Hence, all these companies face the same basic problem. They need personal information on their prospective trade partners—information that enables them to make adequate decisions.

If information asymmetries remain unresolved, trade may break down entirely (Akerlof, 1970). The intuition is that prospective buyers anticipate that a product which a dealer is willing to sell at an average price will be of inferior quality. This reduces their willingness-to-pay for a product of unknown quality and, in equilibrium, only products of the lowest quality are traded. This phenomenon has entered the economic literature as "the lemons problem" has received considerable attention.

One fix to the lemons problem is sometimes referred to as the "certification solution." Here, it is assumed that sellers have the possibility to *voluntarily* provide *credible* information on their type. One intuition for this assumption is that sellers can be legally sued if they provide misleading information, another is that the products can be audited by a competent third party. If the price of such certification is negligible there will be complete unraveling. That means, in equilibrium all types of the seller reveal their information. The only exception is the lowest-quality type, and this type can be identified by the fact that she is the only one who does not reveal. This approach was first suggested by Viscusi (1978). Similar concepts have, for example, been analyzed by Milgrom (1981) or Milgrom and Roberts (1986). Jovanovic (1982) points out that the lemons problem may persist if the costs of the certification process are prohibitively high. Hence, in a game where revelation comes at a positive cost, unraveling may be complete, incomplete or even nonexistent.

If the information to be disclosed is sensitive, unraveling may constitute a severe threat to personal privacy. Consider for example the labor market. Here, agents may have an incentive to provide future employers with detailed information on themselves. This may include details of everyday life, like the ones posted on social networks, or medical records such as drug or pregnancy tests. In a world where (nearly) everybody has the possibility to provide such information, the refusal to do so would be interpreted as a bad signal and unraveling of privacy would take place. From a legal point of view, the unraveling problem is equally important. For instance, Peppet (2011) argues: *"[...] for the field of informational privacy law to remain relevant, it must address the unraveling problem [...]"*.[1]

In the present paper, we analyze unraveling of privacy in a laboratory experiment. We use a labor market with a lemons structure where *workers* have the possibility to provide *employers* with credible information on their *productivity*. We assume that the cost of revelation is strictly positive and we consider several parameterizations where different degrees of unraveling are predicted.

There are two related experiments we are aware of: Forsythe et al. (1989) and the research presented in Chapter 3 of this thesis. Both studies analyze unraveling of private information in experimental lemons markets and they both report that the unraveling is substantial. The first paper focuses on the bidding behavior of the buyers (employers) and addresses unraveling from a general, non-privacy point of view. The experiments are framed neutrally (generic goods and valuations) and the cost of revelation is assumed to be zero. Moreover, there is only one parameterization that is repeated in each period. These aspects may have encouraged the high degree of unraveling reported by Forsythe et al. (1989), and they are in contrast to the second paper. In Chapter 3 not only a loaded labor market frame is used, the setup also comprises different parameterizations and allows for positive costs of revelation. However, the study focuses exclusively on the disclosure behavior of the workers. Employers are not played by actual lab participants, they are substituted by the computer using a suitable payoff function. This may, of course, also influence the degree of unraveling observed.

In Chapter 3 we report that there is a bias toward too little revelation. Workers of rather low productivity generally reveal less frequently than predicted by economic theory. The authors argue that this bias is best explained by using the

[1] Peppet (2011), p. 1203.

level-k rationality model (Nagel, 1995; Stahl and Wilson, 1995),[2] and that it is more pronounced in a treatment using a loaded labor market frame compared to a neutrally-framed treatment. However, on the whole, the deviations are only minor and the theoretic predictions are good predictors for workers' revelation decisions.

In the present study, we close the gap between Chapter 3 and the paper by Forsythe et al. (1989). This is achieved by extending the setup from Chapter 3 in two dimensions. The first extension is that we introduce employers in the game. This might shift unraveling in either direction. For instance, the risk preferences of the subjects who act as employers are crucial. If employers are risk-averse there should be more unraveling compared to the experiments without employers, and if they are risk-seeking there should be less unraveling. The second extension is that we introduce a new parameterization where the cost of revelation is positive but practically negligible. This enables us to control whether or not such costs affect unraveling in a way unforeseen by economic theory.

Our results are in line with the prior studies in that the theory is generally a good predictor of the behavior of our participants. In the final period of our experiments between 65% and 100% of the workers' revelation decisions are in line with the equilibrium. These differences are not exclusively driven by the cost of revelation, but by the parameterization as a whole (i.e., the distribution of types and the cost of revelation). While reducing the cost of revelation to a negligible degree results in a dramatic increase in revelation rates, as predicted by economic theory, this does not necessarily hold for the degree of equilibrium-consistency. In both cases, there exist parameterizations with a high degree of equilibrium-consistency as well as parameterizations with a low degree of equilibrium-consistency.

Overall, the revelations rates we observe in our experiments are similar to those reported in Chapter 3. This is, however, not to suggest that the introduction of employers did not affect the results. We find that high-productivity types reveal more frequently if employers are played by lab participants whereas low-productivity types reveal less frequently. The behavior of the high types will be explained by fairness considerations of the worker. The reason why low types reveal less frequently is rooted in the bidding behavior of the employers.

The remainder of this chapter is organized as follows: Section 4.2 discusses the theoretic aspects of the game with employers and derives the equilibrium predictions. Section 4.3 describes the experimental design and procedures and comments on the parameterizations used in the experiment. In Section 4.4, we derive a few behavioral hypotheses. The results are presented in Section 4.5 and discussed in Section 4.6. Section 4.7 concludes.

[2] Quantal Response Equilibrium (McKelvey and Palfrey, 1995) and Inequality Aversion (Fehr and Schmidt, 1999) predict similar patterns.

4.2 The Game

There are three players: one worker and two employers, and there are n different types of the worker. These types are heterogeneous with respect to their *productivity* θ which is drawn from a *set of possible productivities* $\Theta = \{\theta_1, \theta_2, ..., \theta_n\}$ with $\theta_1 < \theta_2 < ... < \theta_n$. The exact realization θ is ex ante private information of the worker, but the set Θ and the fact that all possible productivities are equally likely are common knowledge. The employers will competitively bid wages in order to hire the worker. They are identical and move simultaneously. All players are assumed to be risk neutral.

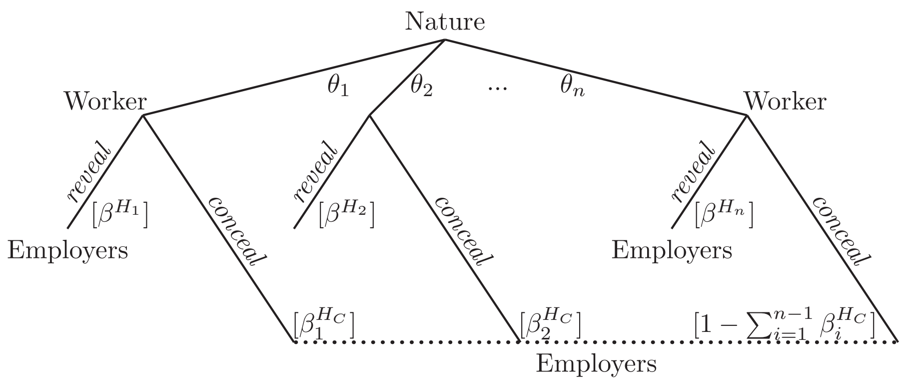


Figure 4.1: Structure of the revelation game.

There are four stages in the revelation game. The first two stages are depicted in Figure 4.1. In stage zero, nature determines the worker's type. In stage one, the worker decides whether or not to disclose her type (in other words, whether to reveal or to conceal her productivity) to the employers. A revelation strategy of the worker is denoted by $\sigma = \{\sigma_1, ..., \sigma_n\}$ where $\sigma_i \in [0; 1]$ is the probability that the worker will choose to reveal as type θ_i. In stage two, the employers simultaneously bid wages in order to hire the worker. Employers' bidding strategies are denoted by $b(H)$ where H refers to the different information sets the employers may reach. In the third stage, the worker accepts one of the offers she received. This could be endogenized in a model where the worker has a third (outside) option which yields a payoff lower than θ_1.

Players' payoffs can be summarized as follows: a worker accepting an employer's bid will receive that bid as a wage payment but, if applicable, she has to pay the cost of revelation. The employers have an endowment γ that is independent of their decisions. However, all further profits depend on whether or not an employer hires the worker (determined by whose bid is accepted). If b denotes the wage bid accepted by the worker, while c and θ represent the cost of revelation and the worker's productivity, respectively, the profits of the worker (π_w) and the employers (π_e) are given by:

$$\pi_w = \begin{cases} b & \textit{if worker conceals} \\ b-c & \textit{if worker reveals} \end{cases} \qquad \pi_e = \begin{cases} \gamma+\theta-b & \textit{if bid was accepted} \\ \gamma & \textit{otherwise.} \end{cases}$$

The employers need to form a system of beliefs specifying a probability $\beta_x^H \in [0;1]$ to all decision nodes x in information set H with $\sum_{x\in H}\beta_x^H = 1$ for all information sets $H \in \mathcal{H}$, where $\mathcal{H}$ is the set of employers' information sets. From Figure 4.1 we learn that employers have $n+1$ information sets including n singletons that are reached upon revelation. These information sets are denoted by $H_1, ..., H_n$ where H_i is the information set where the worker is of type θ_i. At $H_1, ..., H_n$ employers' beliefs are trivially equal to one. In our formal notation, that is $\beta^{H_1} = ... = \beta^{H_n} = 1$. The only non-singleton information set is labeled H_C, and it is reached if the worker chooses to conceal. Here, employers need to form non-degenerate beliefs, i.e., they need to assign a probability to each of the n decision nodes. Let $\beta^{H_C} = \{\beta_1^{H_C}, ..., \beta_n^{H_C}\}$ denote the employers' belief at H_C where $\beta_i^{H_C}$ is the probability the employer assigns to being matched with a worker of type θ_i. Reaching the non-singleton H_C is on the equilibrium path since at least type θ_1 will conceal in equilibrium.[3] Hence, the beliefs can be calculated using Baye's rule. Employers' beliefs after reaching the information set H_C are therefore given by:

$$\beta^{H_C} = \left\{ \beta_1^{H_C}, ..., \beta_n^{H_C} \;\middle|\; \beta_i^{H_C} = \frac{1-\sigma_i}{\sum_{j=1}^n 1-\sigma_j} \;\forall\, i \in \{1, ..., n\} \right\}$$

The revelation game is a dynamic game with incomplete information such that the Perfect Bayesian Equilibrium (PBE) is an appropriate solution concept. In such an equilibrium, players' strategies have to be sequentially rational, and beliefs need to be consistent with the strategies on the equilibrium path.[4] Hence, any PBE of the revelation game comprises the following components:

(i) The worker's revelation strategy σ: a function mapping Θ into reveal decisions.

(ii) The employers' bidding strategy $b(H)$: a function mapping all information sets $H \in \mathcal{H}$ into bids.

---

3 As θ_1 imposes a lower bound on the expected productivity, type θ_1 earns $\theta_1 - c$ when revealing and at least θ_1 when concealing. Hence, for positive costs of revelation, type θ_1 will always prefer concealing to revealing.

4 In the present paper, we use the concept "weak perfect Bayesian equilibrium" as defined in Section 9.C of Mas-Colell, Whinston, and Green (1995). Here, off-the-equilibrium beliefs are not required to be consistent with players' strategies as in other equilibrium concepts such as sequential equilibrium (compare p. 288). However, in the revelation game, this does not play a role as the only information set where beliefs are non-trivial is on the equilibrium path.

(iii) The worker's acceptance strategy: a function mapping bids into accept decisions (not formalized further for brevity).

(iv) A system of beliefs $\beta = \{\beta^{H_1}, ..., \beta^{H_n}, \beta^{H_C}\}$ as described above.

In the third stage, the worker will accept the higher wage if the employers choose different bids or any bid if they are identical. As a consequence, in the second stage, employers will bid the observed productivity if the worker chose to reveal, as the corresponding information sets are all singletons. If the worker concealed her productivity, employers need to base their decision on their beliefs β^{H_C} and will bid the expected productivity given β^{H_C}. Hence, employers will choose the following bidding function in equilibrium:

$$b(H) = \begin{cases} \theta_i & \text{if} \quad H = H_i \text{ with } i \in \{1, ..., n\} \\ \sum_{j=1}^{n} \beta_j^{H_C} \theta_j & \text{if} \quad H = H_C \end{cases}$$

These bidding strategies imply that the worker will receive the entire (expected) rent, independent of her revelation decision. The employers gain nothing from hiring the worker. Apart from their endowment γ, they will both receive zero (expected) profits, independent of whether or not their bid is accepted.

In equilibrium, the worker's revelation strategy σ will have a special pattern. The first few types will choose to conceal while the last few types prefer to reveal. Assume w.l.o.g that m is the highest wage either of the employers offer after observing concealment. If type θ_j prefers concealing to revealing for a given amount m, all other types θ_i with $\theta_i < \theta_j$ prefer to conceal as well. If θ_j prefers to conceal, we have $\theta_j - c \leq m$. If this inequality is satisfied for θ_j, it is also satisfied for all types with lower productivities, i.e., for all $\theta_i < \theta_j$. An analogous argument can be made for the case where θ_j and all types of higher productivities prefer to reveal. Hence, for any realization of m there will always be exactly one threshold $k \in \{1, ..., n\}$ such that all types θ_i with $i \leq k$ weakly prefer concealing to revealing, while all types θ_j with $j > k$ strictly prefer revealing to concealing. Note that depending on m, type θ_k herself may also be indifferent between revealing and concealing. As a consequence, in any PBE of the revelation game, the worker's revelation strategy σ has the form:

$$\sigma = \{\sigma_1 = ... = \sigma_{k-1} = 0, \sigma_k, \sigma_{k+1} = ... = \sigma_n = 1\}$$
$$\text{with } k \in \{1, ..., n\} \text{ and } \sigma_k \in [0; 1].$$

Applying this form of the worker's revelation strategy to the employers' system of beliefs as defined above, we obtain employers' beliefs upon observing concealment:

$$\beta^{H_C} = \left\{ \beta_1^C = ... = \beta_{k-1}^C = \frac{1}{k - \sigma_k}, \beta_k^C = \frac{1 - \sigma_k}{k - \sigma_k}, \beta_{k+1}^C = ... = \beta_n^C = 0 \right\}$$

and their bidding function:

$$b(H) = \begin{cases} \theta_i & \textit{if} \quad H = H_i \text{ with } i \in \{1, ..., n\} \\ \dfrac{(1 - \sigma_k)\theta_k + \sum_{j=1}^{k-1} \theta_j}{k - \sigma_k} & \textit{if} \quad H = H_C \end{cases}$$

The revelation strategy σ, the bidding function $b(H)$, the verbal description of the worker's acceptance strategy, and employers' set of beliefs β define a PBE of the revelation game, if σ constitutes a best response for each type of the worker given the employers' set of beliefs β and bidding function $b(H)$.

The equilibria depend on the parameters Θ and c which define the threshold k and the corresponding σ_k. Note that the equilibria and the thresholds k are not necessarily unique. If there are several thresholds k, the game will also have multiple equilibria. This does not, however, occur in the parameterizations used in the experiments.[5] However, multiplicity of equilibria may also arise even if there is only one threshold k. Whenever there is an equilibrium system of beliefs resulting in a bid after observing concealment leaving type θ_k indifferent between revealing and concealing (i.e., $b(H_C) = \theta_k - c$), there will be up to three equilibria: one where θ_k conceals ($\sigma_k = 0$), one where θ_k reveals ($\sigma_k = 1$) and possibly one where θ_k chooses a completely mixed strategy with $\sigma_k \in]0; 1[$.[6] This also occurs in one of the combinations we use in the experiments. In Section 4.3 the corresponding parameterization is introduced as *High Cost—Market C* and the equilibria are described in Table 4.1 of that Section.

4.3 Experimental Design and Procedures

In the experiments, a random matching routine was used in combination with a fixed-roles-but-random-types design. In each session, there were 18 participants who were divided into twelve employers and six workers. This role assignment remained constant during the entire experiment, the productivity of the workers and the matching were, however, subject to change at the beginning of each

5 A example with multiple thresholds is the parameterization $\Theta = \{200, 401, 402, 435\}$ and $c = 100$. In this case there are four equilibria: (i) $k = 4$, $\sigma = \{0, 0, 0, 0\}$ and $b(H_C) = 359.5$, (ii) $k = 4$, $\sigma = \{0, 0, 0, 0.98\}$ and $b(H_C) = 335$, (iii) $k = 3$, $\sigma = \{0, 0, 0.97, 1\}$ and $b(H_C) = 302$ and (iv) $k = 1$, $\sigma = \{0, 1, 1, 1, 1\}$ and $b(H_C) = 200$.

6 Typically, there will indeed be three equilibria: two in pure strategies and one in mixed strategies. The mixed equilibrium may, however, coincide with either of the pure-strategy equilibria such that an equilibrium where type θ_k chooses a completely mixed strategy is not bound to exist.

period. Note that the random matching only determined which employers interacted with which workers, and that there were always the same six workers in one session.

We used six different parameterizations, each comprising a set of six possible productivities. The productivity of a worker was determined by a random draw of the computer,[7] where each of the six possible productivities was chosen with equal probability. The random draw was conducted without replacement, such that each of the six possible productivities was attributed to exactly one worker in each period (as was mentioned in the instructions). Finally, six groups, each consisting of two employers and one worker, were randomly formed by the computer at the beginning of each period. Because of the random matching we conservatively count one session of 18 subjects as one independent observation.

The timing of the base game was as described in Section 4.2. The matching took place at the beginning of each period and the productivities of the workers were also determined then. Afterwards, everybody was presented the parameterization to be played that period, and workers were informed about their productivities. In the first stage, workers decided whether or not to disclose their productivities. In the second stage, employers were informed of the decision of the worker in their group and needed to simultaneously bid wages for that worker. The support for the wage bids was the interval $[0; 800]$, it did not depend on the current parameterization or the decision of the worker. In the third stage, the workers had to accept one of the two wage bids they had received. Finally, subjects were given a summary of the results in that period. Nobody received any information about the decisions of players outside their group.

Subjects' payoff functions were equivalent to the ones presented in Section 4.2. In the experiments, employers received an endowment of $\gamma = 200$ ECU each period to avoid biased behavior due to zero profits or losses.

In the course of the experiment, we considered two different treatments labeled *High Cost* (or HC) and *Low Cost* (or LC) where the cost of revelation c is varied. In HC, disclosing one's productivity comes at a cost of $c = 100$. In LC, these costs are reduced to $c = 1$. Apart from that, everything was identical in these treatments. HC and LC were conducted using a between-subjects design, i.e., subjects that participated in HC did not participate in LC and vice versa.

Apart from the variation of the cost of revelation, we also varied the set of possible productivities (labeled Θ in Section 4.2). The different parameterizations were referred to as *markets* and were addressed using a within-subjects design. That is, they were played on a rotating basis.[8] Subjects played six repetitions of each market such that there were 18 periods in total. The only difference between

[7] The experiments were conducted using the usual combination of zTree software package (Fischbacher, 2007) and the on-line recruitment system provided by Greiner (2004).

[8] Subjects started by playing *Market A* in the first period, then turned to *Market B* and *Market C* in the second and third period, respectively. Afterwards, the process began again with *Market A*.

the markets was the set of possible productivities Θ.

Market A

Θ	LC σ	LC β^{Hc}	HC σ	HC β^{Hc}
200	0	1	0	$\frac{1}{5}$
210	1	0	0	$\frac{1}{5}$
230	1	0	0	$\frac{1}{5}$
260	1	0	0	$\frac{1}{5}$
300	1	0	0	$\frac{1}{5}$
600	1	0	1	0
k	1		5	
σ_k	0		0	
$b(H_C)$	200		240	

Market B

Θ	LC σ	LC β^{Hc}	HC σ	HC β^{Hc}
200	0	1	0	1
448	1	0	1	0
510	1	0	1	0
551	1	0	1	0
582	1	0	1	0
607	1	0	1	0
k	1		1	
σ_k	0		0	
$b(H_C)$	200		200	

Market C

Θ	LC σ	LC β^{Hc}	HC1 σ	HC1 β^{Hc}	HC2 σ	HC2 β^{Hc}	HC3 σ	HC3 β^{Hc}
200	0	1	0	$\frac{1}{3}$	0	$\frac{1}{2}$	0	$\frac{5}{12}$
280	1	0	0	$\frac{1}{3}$	0	$\frac{1}{2}$	0	$\frac{5}{12}$
360	1	0	0	$\frac{1}{3}$	1	0	$\frac{2}{5}$	$\frac{2}{12}$
440	1	0	1	0	1	0	1	0
520	1	0	1	0	1	0	1	0
600	1	0	1	0	1	0	1	0
k	1		3		3		3	
σ_k	0		0		1		0.4	
$b(H_C)$	200		280		240		260	

Table 4.1: Parameterizations used in the experiment and the corresponding PBE.

Table 4.1 summarizes the productivities and equilibrium predictions for the three markets in both treatments. We use the notation introduced in Section 4.2. Apart from the thresholds k and σ_k, we also report the revelation strategy of the worker σ and employers' beliefs and bids upon observing concealment. There is always a unique equilibrium except for Market C in High Cost where we have three equilibria. In the table, these equilibria are denoted by HC1, HC2 and HC3. In the remainder of this paper, we only refer to HC1 and we neglect the other equilibria. HC1 is the one best in line with the experimental data, and the deviations would only be larger when comparing the data to the other equilibria.

In the present paper, we also compare our findings from the *game with employers* to the results we presented in Chapter 3 where we considered the *game without employers*. There are several differences between these experiments. For instance, in Chapter 3 a health-related framing was used—a worker's productivity was referred to as a *health condition* and not just as productivity as in the current study. There were also fewer repetitions of the base game (only five repetitions of each market or 15 periods in total). However, the most prominent difference is that in Chapter 3 employers were substituted with a suitable payoff function. In the game without employers, workers received their own productivity minus the cost of revelation if they decided to reveal, and the average productivity of all concealing workers if they decided not to reveal. The equilibrium revelation rates in the game without employers are identical to the ones we derived for our High Cost treatment (see Table 4.1). This enables us to compare workers' revelation behavior in both setups despite the differences between the games. In the present paper the data from the game without employers is referred to as *No Employers* or NE.

The experiments using the game with employers (HC and LC) were conducted at the *DICELab* on the campus of the *University of Düsseldorf*. A total of 108 participants took part in these experiments, 54 of these in HC and LC, respectively. One session of the game with employers comprises 18 subjects, six workers and twelve employers. Because of the random matching, one session counts as one independent observation. Hence, we gathered a total of three independent observations for either treatment.

In the experiments with employers, we elicited subjects' risk preferences by using Holt and Laury's (2005) paired lottery choices[9] before subjects played the revelation game. In order to exclude wealth effects, participants were not informed about the outcomes of the lotteries until the very end of the experiment.

Subjects' earnings from the revelation game were aggregated over the 18 periods and converted into Euro at an exchange rate of ECU 400 equaling €1. At the end of the experiment, subjects simultaneously received their payments from the revelation game and from the risk elicitation task. Average earnings were about €15.66 for an experiment that lasted about 90 minutes.

The data for the game without employers originates from the study presented in Chapter 3. The corresponding experiments took place in the lab at the *Technical University Berlin*. One session lasted about 60 minutes and another 72 subjects participated in these experiments.[10] Average earnings in the simultaneous game were about €10.76. Note that risk preferences were not elicited in the experiments without employers.

4.4 Hypotheses

We expect revelation rates in Low Cost to be higher compared to the High Cost treatment. This expectation is in line with the theoretical predictions which suggest a global revelation rate of 83.33% in LC compared to only 50% in HC. The reason for this is as follows. The higher the cost of revelation, the fewer the types will have an incentive to reveal. Low-productivity types in particular would not find it in their interest to reveal their type if the cost of revelation was high.

Hypothesis 1. *Revelation rates in LC will be higher compared to HC.*

The revelation rates will be lowest in Market A and highest in Market B in both our treatments. In HC, this pattern is in line with the predictions. Here, the equilibrium revelation rates are 16.67%, 83.33% and 50% for the markets A, B and C, respectively. This is in contrast to LC where the predicted rates are identical for all markets. However, there is still considerable variation in workers'

[9] We employ an incentivized version of their "Low Payoff" lotteries without actually converting the amounts from \$ to €, i.e., we pay subjects €2 whenever Holt and Laury (2005) would have paid them \$2.

[10] In Chapter 3, the data used here is referred to as *Loaded_Base*.

incentives to stick to their equilibrium actions. For instance, when deviating from revelation, a type-2 worker looses ECU 9 in Market A compared to ECU 79 and ECU 247 in the markets C and B, respectively. Similar trade-offs also exist for the other types that should conceal in HC, but not in LC. Hence, we expect the ranking of revelation rates across markets to be identical in both treatments.

Hypothesis 2a. *In HC, the degree of unraveling will be highest in Market B and lowest in Market A.*

Hypothesis 2b. *In LC, the degree of unraveling will be highest in Market B and lowest in Market A.*

We expect to observe a positive correlation between the revelation rate and the productivity of the worker. This hypothesis is also consistent with economic theory. In our parameterizations, all types of the worker choose pure strategies in equilibrium. Since any pure-strategy equilibrium of the revelation game includes concealment of the first few types and revelation of types with higher productivities, the experimental data should show that low-productivity types reveal at lower frequencies compared to high-productivity types.

Hypothesis 3. *In all treatments and in all markets, we expect the revelation rates to increase in the type of the worker.*

There will be a systematic bias involving significantly less revelation than predicted by the equilibria. This is consistent with prior evidence, presented in Chapter 3. The authors report that low-productivity workers frequently choose to conceal even though they should reveal in equilibrium. We expect the same pattern to occur in the game with employers. In order to realize that they have an incentive to reveal, types of rather low productivity need to anticipate that employers expect the higher types to reveal. The higher the type of a worker, the fewer decisions have to be anticipated to find the own equilibrium action. As a consequence, low-productivity types who should reveal in equilibrium are more likely to deviate from that prediction compared to types of higher productivity.

Hypothesis 4. *Types who should reveal in equilibrium will deviate from their prediction more frequently than types who should conceal in equilibrium.*

We expect types with high productivities to conceal less frequently in the game with employers compared to the game without employers. In the game without employers, fairness considerations may play a role, as revelation creates payoff asymmetries between the different workers. Here, high-productivity workers can reduce these asymmetries by concealing. In the game with employers, there may also be substantial differences concerning subjects' payoffs, but there are two reasons why this should not affect the revelation decisions. First, workers' fairness considerations will more likely concern the payoffs of the employers in their experimental group. There may be substantial differences between these payoffs. The inequality is, however, created by employers' bids and by the fact that only one employer can hire the worker. Second, the wages for other workers are determined by other employers' wage bids and are therefore not directly influenced by the worker's revelation decision. Hence, in the game with employers, fairness considerations should not prevent workers from revealing. Switching to concealment reduces neither the inequality between workers and employers nor the inequality between different workers.

Hypothesis 5. *High-productivity types will reveal more frequently in HC compared to NE.*

If the worker chooses to reveal her type, employers will make a positive profit from hiring the worker. In other words, their wage bids will be lower compared to the predictions. This is in line with prior evidence found by Dufwenberg, Gneezy, Goeree, and Nagel (2007) who observe analogous behavior in experimental Bertrand duopolies. The intuition is as follows. Since the equilibrium wage bids imply that the entire pie is allotted to the worker, employers have little incentive to stick to their equilibrium action. Even from a theoretic point of view, bidding the productivity of the worker is weakly dominated by all lower bids. As a consequence, we expect employers to bid less than the observed productivity of the worker, whenever the worker chooses to reveal.

Hypothesis 6. *Employers' wage bids will be lower than the worker's productivity if the worker chooses to reveal.*

The same logic does not necessarily apply for the case of concealment. Here, employers do not know the exact value of the worker's productivity, and they will typically have non-degenerate beliefs about the type of the worker they are matched with. Moreover, it is possible that the employers in one experimental group have different beliefs about the productivity of a concealing worker. Hence, there is a chance that employers make positive profits, even if they bid the expected productivity given their beliefs. This occurs if the other employer mistakenly anticipates a lower productivity. Thus, one could expect employers' behavior to be in line with the predictions if the worker chooses to conceal.

Hypothesis 7a. *Employers' bids upon observing concealment will correspond to the expected productivity of the worker given the workers' actual revelation behavior.*

However, there are also reasons why employers' bids might be biased in either direction. On the one hand, risk-aversion may cause employers to bid less than the productivity they actually expect. If this is the case, employers' bids upon observing concealment should correlate with their decisions in the Holt and Laury (2005) part. On the other hand, even with risk-neutrality, employers may also find themselves in a situation where they end up paying more than intended. The reason is that beliefs will presumably vary across subjects, and as workers will usually select the higher bid the resulting market wage might be rather high. A similar, well-known effect that arises in first-price-sealed-bid-common-value auctions is called *the winner's curse*.[11]

Since there are reasons why employers' bids might be unbiased as well as reasons why they might be biased in either direction we formulate one hypothesis for each case. The following hypotheses are not only mutually exclusive, they also contradict our Hypothesis 7a. We expect one of these three hypotheses to hold.

Hypothesis 7b. *Employers' bids upon observing concealment will be lower compared to the expected productivity of the worker given the workers' actual revelation behavior.*

Hypothesis 7c. *Employers' bids upon observing concealment will be higher compared to the expected productivity of the worker given the workers' actual revelation behavior.*

4.5 Results

In this Section we present our experimental results. It is structured as follows. In Section 4.5.1 we describe the revelation behavior of the workers. This subsection is split into two parts. In Section 4.5.1 we compare the High Cost and the Low Cost treatments, and in Section 4.5.1 the games with and without employers are compared. The behavior of the employers is described in Section 4.5.2. Section 4.5.3 comments on the development of decisions over time.

In total, we have twelve independent observations for the game without employers (NE) and three independent observations for either treatment of the game with employers (HC and LC). The reason for this discrepancy is that one independent observation for the game with employers comprises three times as many participants as one observation for the game without employers (twelve employers and six workers instead of just six workers).[12]

[11] See for instance Klemperer (2004) for a theoretical description of the winner's curse. Kagel and Levin (1986) and Lind and Plott (1991) provide experimental evidence for the curse to occur in laboratory experiments. More recently, Eyster and Rabin (2005) introduced a behavioral model allowing for varying degrees of *cursedness*. Crawford and Iriberri (2007) formulate another model where the winner's curse is linked to level-k rationality.

[12] In the game without employers, we use a fixed matching such that one session with 24 workers results in four independent groups, each comprising the decisions from six workers. In HC and in LC, one session with twelve employers and six workers results in only one independent observation. We use a random matching to determine which employers interact with which worker. However, the composition of the six workers in one session of the game with employers is just as fixed as the composition of the six workers within one group of the game without employers. Hence, it is possible to compare group-level data from the game without employers to session-level data from the game with employers.

4.5.1 Workers' decisions

The workers' revelation decisions from all experiments are summarized in Figure 4.2. Each chart depicts the share of workers that choose to reveal as a certain type in a certain market in one of the three treatments. The charts are arranged such that the rows contain the observations from our markets A, B and C, and the columns summarize the different treatments. The exact values underlying the figure can be found in Table 4.3 in the appendix. Note that the charts also contain the equilibrium predictions that are indicated by red markers.

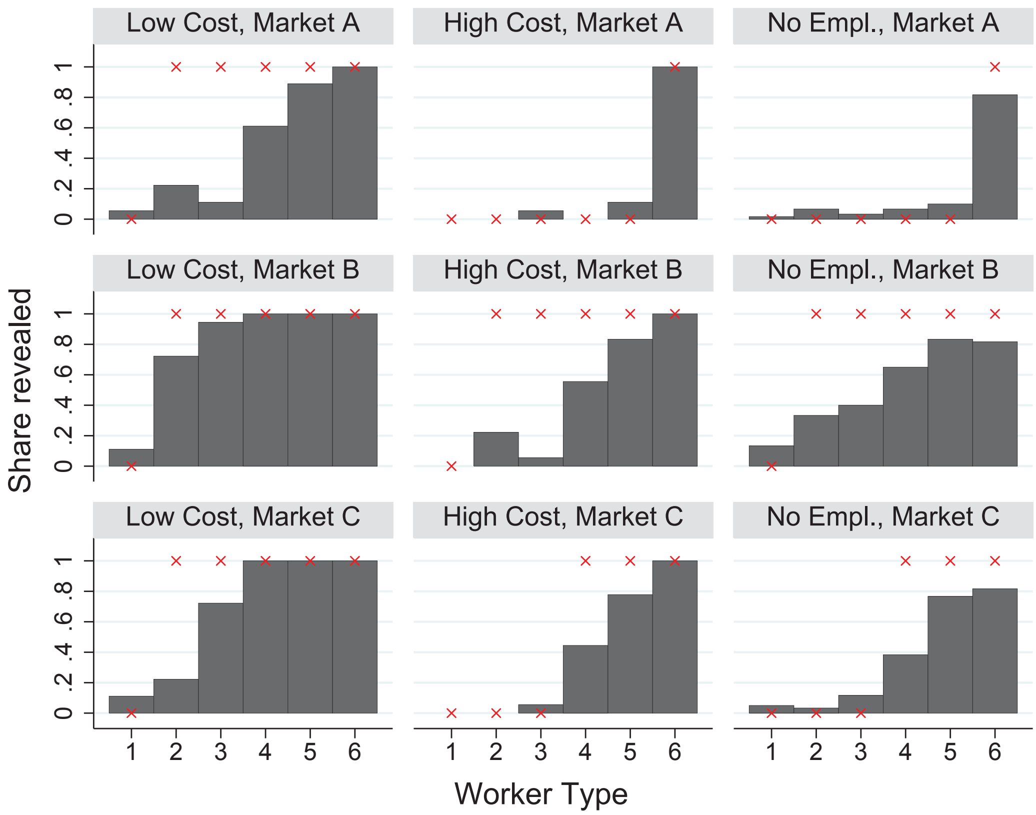


Figure 4.2: Workers' decisions dependent on worker types across all markets and treatments. The red markers indicate the corresponding equilibrium predictions.

HC vs. LC

The data depicted in Figure 4.2 supports our first hypothesis: There is more revelation in High Cost compared to Low Cost. We find that about 65% of the workers' decisions imply revelation in LC compared to only about 34% in HC. This difference is significant at the 5% level (one-sided Mann-Whitney U-test, $p = 0.050$) which is evidence for Hypothesis 1.

As for the different markets, we find support for both Hypotheses 2a and 2b. Our HC data shows that about 19.4%, 44.4% and 38.0% of the workers' decisions imply revelation in markets A, B and C, respectively. In our three HC sessions the average revelation rates were always lowest in Market A and always highest in Market B. This ranking is significant at the 5%-level (one-sided Friedman test, $p = 0.028$). In LC, we observe the same pattern, despite the fact that revelation rates should be identical in equilibrium. However, because of the structure of workers' incentives, this is not entirely unexpected. The ranking for LC is just as significant as the one for HC (one-sided Friedman test, $p = 0.028$).

In the figure, there is also evidence for Hypothesis 3. Types of higher productivities reveal in general at higher frequencies compared to lower types. We find that there is a positive correlation between the workers' types and their revelation decisions. To test this, we calculated Spearman's ρ between the workers' revelation decisions and their type ranks (i.e., rank i, not type θ_i) for our six independent observations and found that ρ is significantly larger than zero (one-sided sign test, $p = 0.016$). In Chapter 3, we reported a similar finding for the simultaneous-move game without employers.

Figure 4.2 also delivers evidence for Hypothesis 4: types who should reveal in equilibrium more often deviate from their equilibrium action than types who should conceal in equilibrium. This is especially obvious in High Cost Market B and Low Cost Market A. Here, 100% and 94% of the types who conceal in equilibrium stick to their equilibrium action compared to only 53% and 57% of the types who reveal in equilibrium. This result may be qualified by the fact that in both parameterizations five out of six types should reveal in equilibrium. However, the only parameterization with a balanced prediction—Market C in High Cost—features numbers of comparable magnitude. Here, we have 98% equilibrium-consistent choices when subjects should conceal compared to about 74% if they should reveal. When averaging across both treatments and all markets, we find that 96% of the types who should conceal actually do so, while only 72% of the types who should reveal choose their equilibrium action. This difference is significant at the 5% level (one-sided Wilcoxon signed-rank test, $p = 0.016$). Unfortunately, the low number of observations prevents us from testing the treatments separately.

HC vs. NE

In this Section, we compare our data to the data for game without employers. Our treatment High Cost is comparable to the game without employers in that the parameterization as well as the equilibrium predictions are identical across these two treatments. This is obviously not the case for the Low Cost treatment, and the corresponding data is therefore excluded from the analyses in the following paragraphs.

We find support for Hypothesis 5 in that revelation rates of type-six workers are higher in HC compared to NE. The data in Figure 4.2 documents that in HC

100% of the revelation decisions by type-six workers imply revelation compared to only about 82% in NE. Both shares are remarkably stable. In No Employers the share of type-six workers choosing to reveal is constant across all three markets, and there is literally no variation concerning these decisions in High Cost. This difference is significant at the 1% level (one-sided Mann-Whitney U-test, $p = 0.006$) and delivers support for our Hypothesis 5.

Further evidence supporting Hypothesis 5 is delivered by probit regressions whose results are summarized in Table 4.2 and visualized in Figure 4.3. Here, we find that low-productivity types reveal less often in the game with employers, while high-productivity types reveal less often in the game without employers.

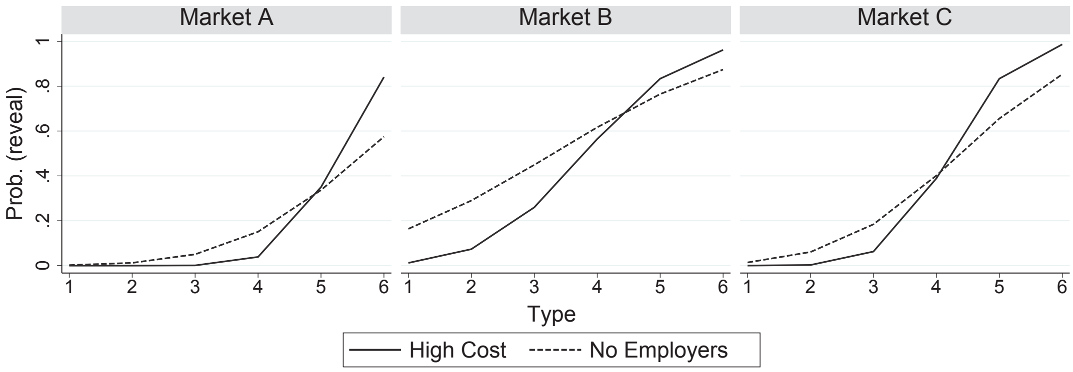


Figure 4.3: Probability of revelation implied by probit regressions.

Consider Figure 4.3 first. The dashed and the solid lines represent the probability that a worker of a specific type will choose to reveal in a given market in No Employers and in High Cost, respectively. In all three markets, we observe that the dashed lines are above the solid lines as long as the worker's type does not exceed four. Hence, low-productivity types are less likely to reveal in High Cost. Then, the lines for HC and NE intersect between types four and five, and the predicted revelation rates for workers of type five and six are higher for HC compared to NE. In other words, high-productivity types are more likely to reveal in High Cost.

The probit regressions were conducted separately for the three markets, and their results are presented in Table 4.2. In Market A, we do not find significant differences between HC and NE. Neither the treatment dummy for High Cost nor its interaction with the worker type is significant. In the markets B and C all regressors are significant. The treatment dummy is significantly negative in both cases. This captures that types of low productivity reveal less frequently in High Cost. The interaction term is significantly positive for both markets indicating more revelation by high-productivity types in High Cost. Also note that the worker type and the interaction term between HC and type are positive in all markets. Thus, the regression results deliver additional support for our

	Market A revealed	Market B revealed	Market C revealed
Type	0.611***	0.425***	0.650***
	(0.132)	(0.0578)	(0.0912)
High Cost	-3.827	-1.661**	-2.435***
	(2.866)	(0.653)	(0.860)
HC*Type	0.773	0.382**	0.601***
	(0.534)	(0.148)	(0.201)
Constant	-3.474***	-1.404***	-2.850***
	(0.699)	(0.209)	(0.379)
Observations	468	468	468

Std. Err. adjusted for 90 clusters (subjects)
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.2: Probit regressions underlying Figure 4.3. Note: the standard errors presented in the table are clustered at the subjects level. Clustering at the group or session level does not change the results qualitatively. In such regressions, all the effects identified are significant at the 1% level.

Hypothesis 2 where we argued that revelation rates should increase with the type of the worker.

While we anticipated the differences observed for high types (Hypothesis 5) because of fairness considerations, there is no such easy explanation for the differences in the behavior of lower types. Low-productivity workers reveal less frequently in the game with employers compared to the game without employers. This is not just a reaction to the changed behavior of the high types. If high types reveal more frequently, types of lower productivities should also reveal more frequently. The intuition is that employers should bid less upon observing concealment because the probability that they are matched with a high type is relatively low. This is in contrast to our experimental data. In Section 4.5.2 we will show that the behavior of the employers is biased in a certain way, and in Section 4.6 we will argue that the behavior of the low types may be a reaction to this bias.

4.5.2 Employers' bids

Figure 4.4 visualizes the market wages and relates them to the productivity of the corresponding worker. The scatter plots depict the average wage bid that was accepted by the worker. The plots also contain information on the standard deviation of these bids. The black entries refer to the cases where the worker reveals her type, the red entries represent concealing workers. In the case of concealment, we use the average productivity of a concealing worker in the corresponding combination of market and treatment. The dashed lines indicate equality of wages and productivity. In theory, all entries should be located on these dashed lines.

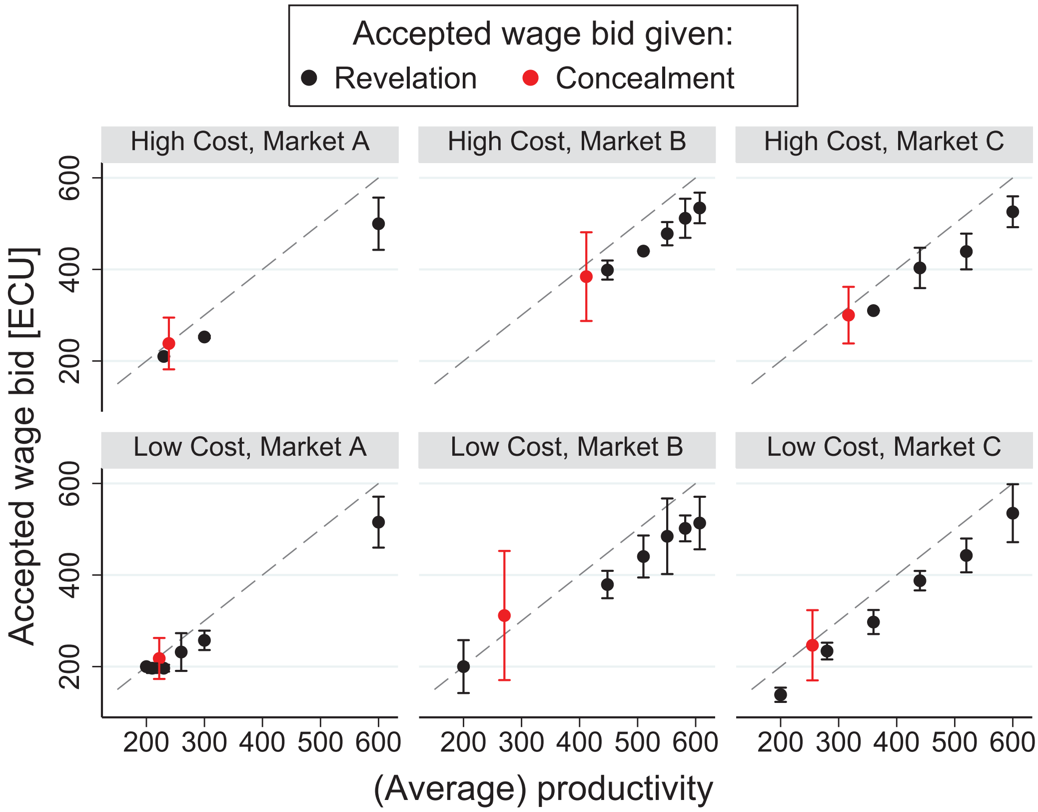


Figure 4.4: Accepted wage bids depending on the information set reached. The black entries represent the singleton information sets $H_1, ..., H_6$ that are reached if a worker of the corresponding type reveals. The red entries represent the non-singleton information set H_C that is reached upon concealment. Note that the productivities of the workers may vary in the case of concealment. Here, the figure uses the ex-post realized average productivity given concealment.

From Figure 4.4 we learn that employers' bids fall behind the worker's productivity if the worker chose to reveal. In most cases, the black entries are considerably below the dashed line. More often than not, the difference between the average accepted wage bid upon revelation and the productivity of the worker is larger than one standard deviation of the wage bid. On average, we find that employers aim for a rent of about ECU 94.70 or 19.13% of the observed productivity of the worker. The employers whose bids were accepted make profits of about ECU 67.76 or 13.42% of the worker's productivity. In the case of revelation, the accepted wage bids are significantly lower than the productivity of the worker (one-sided Wilcoxon signed-rank test, $p = 0.016$). Hence, employers earn positive profits from hiring a worker of known productivity. This supports our Hypothesis 6.

Hiring a worker who chose to conceal is hardly profitable for the employers. Figure 4.4 suggests that average wages and productivities coincide rather well in the case of concealment. All the red entries are close to the dashed line. The differences between the average productivity and the average wage bid appear negligible, especially when compared to the standard deviation of the wage bid. The fact that the average accepted wage bid plus one standard deviation always exceeds the average productivity of a concealing worker, documents that employers often realize losses when they hire a worker who chose to conceal. On average, employers earn about ECU 7.48 if they hire a worker of unknown productivity. In relative terms, employers even make losses when the worker conceals. On average, they realize a margin of about -5.24% of the worker's productivity.[13] If the worker chose to conceal, accepted bids are not significantly different from the productivity of the worker (one-sided sign test, $p = 0.656$). This supports Hypothesis 7a.

As employers' profits after concealment are lower compared to their profits after revelation, it appears unlikely that differences in their behavior are driven by risk preferences as suggested by Hypothesis 7b. To nevertheless test for a correlation, we choose the following approach.[14] We calculate Spearman's ρ between an employer's average bid upon concealment and her number of risky choices in the Holt-Laury task. Without controlling for the market or the treatment, we have $\rho = 0.12$, which is not a significant correlation ($p = 0.346$). Repeating the same procedure for each combination of treatment and market separately also does not reveal any significant correlation. The values for ρ are between -0.09 and 0.25 and the p-values range from 0.132 to 0.759. Hence, we reject Hypothesis 7b.

As for Hypothesis 7c, we find no significant differences between employers' average bids upon concealment and the average productivity of the corresponding workers. As a consequence, employers in the revelation game do not experience a winner's curse in that there is systematic over-bidding given the revelation behavior of the workers. This is in contrast to prior experiments. Eyster and Rabin (2005) analyze the data from Forsythe et al. (1989) and find evidence of cursedness in the case of concealment. One reason for this discrepancy between Forsythe et al. (1989) and the present study might be that there were more (four)

---

13 The relative profits may be negative even though the absolute profits are positive. For instance, assume there are only two cases. In the first case an employer hires a type-six worker for a wage of zero. Her profits will be ECU +600 in absolute terms or +100% of the worker's productivity. In the second case, a type-two worker is hired for the wage of a type-six worker. This employer's profits will be ECU -400 or -300% of the workers productivity. In this example, the average relative profits are -100% even though employers earn on average ECU 100.

14 Note that 14 out of 108 subjects gave inconsistent answers in the Holt-Laury task and were therefore excluded from the analysis.

bidders in Forsythe et al.'s (1989) experiments. For instance, Kagel and Levin (1986) report that the winner's curse is especially strong in experiments with a lot of bidders.

4.5.3 Learning

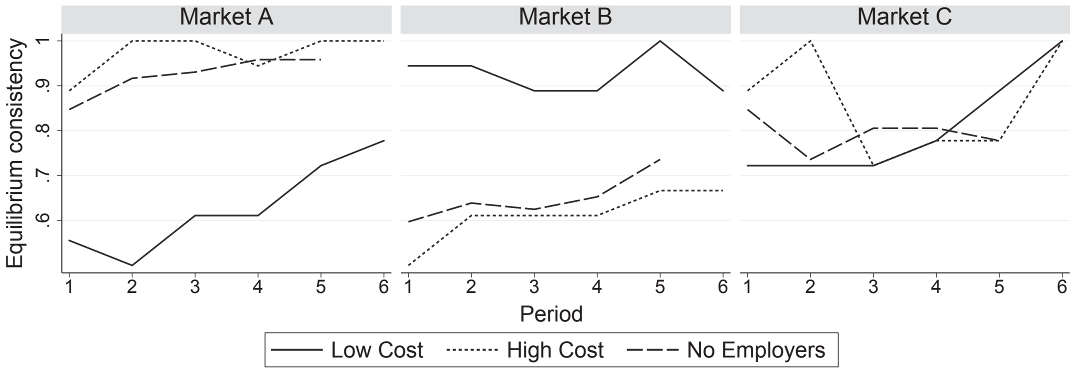


Figure 4.5: Equilibrium consistency of workers' revelation decisions over time.

There is moderate learning in our experiments. Figure 4.5 visualizes the development of the share of workers opting for their equilibrium action over time. As shown in the figure, this share is superior in later periods. In the final period, between 65% and 100% of all revelation decisions are in line with the theoretic predictions. Averaging across the markets, we find that in both treatments with employers (LC and HC), 88.89% of the workers' revelation decisions in the final period are in line with the predictions. In NE this share is 82.41%.

There appears to be better learning in the experiments with employers. In both treatments, equilibrium consistency increases by about 15%. This is in line with Forsythe et al. (1989) who also emphasize that there is more unraveling in later periods.

In general, Figure 4.5 documents that the theoretic predictions capture workers' revelation behavior rather well. A majority of workers' decisions are in line with the predictions. In some cases, all or nearly all workers behave according to the predictions. However, having said that, it should be noted that there are also some exceptions. For instance, in Market B in HC, about 35% of the decisions depart from the predictions in the final period. Given the pattern of the revelation rates depicted in Figure 4.2, this implies that three out six worker types manage to pool even though they should not be able to do so.

There is one further interesting aspect concerning the degree of equilibrium consistency. It does not exclusively depend on the cost of revelation. In the markets A and C, the share of equilibrium-consistent revelation decisions is significantly higher in High Costs compared to Low Cost while the opposite is true in Market B. Here, the share of equilibrium-consistent revelation decisions is higher in Low Cost compared to High Cost (one-sided Mann-Whitney U tests, $p = 0.050$ in all three cases).

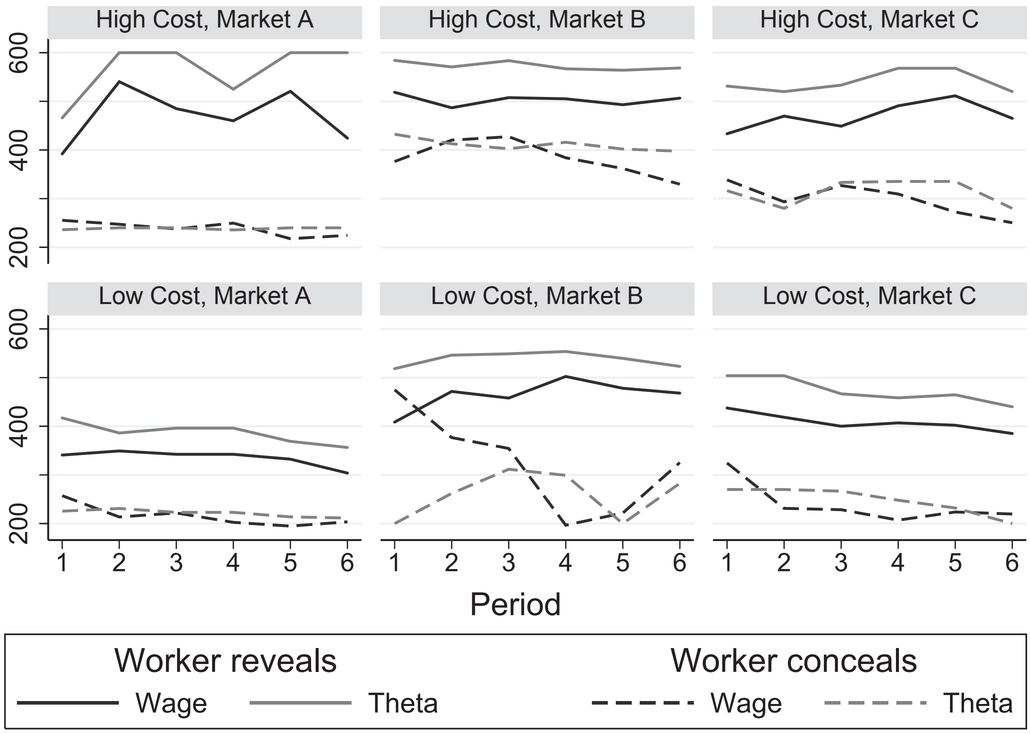


Figure 4.6: Equilibrium consistency of workers' revelation decisions over time.

Figure 4.6 visualizes the development of the market wages (i.e., the bids accepted by the workers) and relates them to the average productivity of the workers. The solid lines capture the case where the worker chose to reveal, the dashed lines represent cases where the worker concealed.

The figure documents that the differences in the profits employers realize when hiring workers that revealed or concealed, are stable over time. In Section 4.5.2 we reported that employers realize positive profits in the case of revelation, but not in the case of concealment. From Figure 4.6 we learn that this effect does not alleviate over time. Throughout our experiments, the average market wages fall behind the average productivity in the case of revelation, whereas average wages and average productivities coincide rather well in the case of concealment.

4.6 Discussion

The differences in the profits employers can realize depending on the worker's revelation decision have an important implication for unraveling. If the worker chooses to reveal, employers manage to extract positive rents from hiring the worker. As they are unable to do so if the worker conceals, the profits employers can realize upon revelation can be considered as an additional, endogenous cost of revelation which workers have to pay whenever they choose to reveal. Therefore, fewer workers will find it in their interest to reveal their productivity. As the cost of revelation increases, the threshold k we used to define the highest type of the worker that chooses to conceal in equilibrium, will also increase. Hence, workers of low productivity in particular will reveal less frequently in the game with employers compared to the game without employers. Note that this is perfectly in line with the workers' revelation behavior as reported in Section 4.5.1.

Such endogenous costs of revelation may explain why unraveling is not necessarily complete even if the exogenous cost of revelation is negligible as in Low Cost. From Figure 4.6 we learn that the profits employers realize upon revelation are rather constant across treatments and markets. As noted above they are roughly ECU 68 on average. Taking this amount into account when deriving the equilibria results in different equilibrium predictions. For instance, assume that workers actually have to pay ECU 69 instead of ECU 1 in Low Cost. In this case, the equilibrium predictions change as follows. In Market A there is an equilibrium where only the types five and six reveal, in Market C type two may deviate to concealment and the predictions for Market B remain unaffected. Even though these new predictions do not match the observed revelation rates perfectly, they still capture the experimental data far better than those predictions that do not account for the positive profits employers receive in the case of revelation.

4.7 Conclusion

In this paper, we analyze workers' willingness to disclose private information in a lab experiment. This research is closely connected to the work presented in Chapter 3. By using a similar game with a similar parameterization we extend Chapter 3 in two dimensions and close the gap to Forsythe et al.'s (1989) experiments.

In general, the results reported in Chapter 3 are robust when the cost of revelation is nearly zero, or when employers are introduced. In both our treatments, the experimental data features the same basic patterns. We find a similar correlation between the revelation rates and the worker's productivity and the same systematic bias toward too little revelation. In both studies, types who should reveal in equilibrium deviate from their equilibrium action more frequently than other types. In our experiments this effect is driven by types of lower productivities—as was the case in Chapter 3.

Comparing the games more precisely, we find that the effect of introducing employers is inconclusive whereas the consequences induced by their behavior are unambiguous. Employers' wage bids impede unraveling. However, in the game with employers, high-productivity types reveal more frequently, and low types reveal less frequently compared to the game without employers. The reasons for this are as follows.

High-productivity types reveal more frequently because fairness considerations are less important in the game with employers. In the game without employers, concealment is a possibility for high types to reduce the inequality between them and the other workers. This possibility exists because the payoff of a concealing worker depends directly on the decisions of all other types. This is not the case in the game with employers where workers' wages are determined by employers' bids. Here, literally all type-six workers disclose their private information compared to only about 80% in the game without employers.

The reason why low-productivity workers reveal less frequently is found in the bidding behavior of the employers. Our data documents that they manage to extract positive rents if the worker chooses to reveal but not if she chooses to conceal. This can be interpreted as an additional cost that arises whenever a worker chooses to reveal. Such an additional cost of revelation reduces the number of workers who have an incentive to reveal their type. Low types in particular often find it prohibitively high and deviate to concealment. This can be shown by deriving predictions that account for employers' profits. We find that such predictions are much more in line with the experimental data than the standard equilibria.

Our experiments document that the degree of unraveling is substantial. In our Low Cost treatment, the cost of revelation is practically zero such that workers face truly strong incentives to reveal their data. We find that revelation rates increase dramatically. For instance, in our Market B everybody except for the lowest type reveals very frequently such that unraveling is nearly complete. Averaging across all markets, we find that the revelation rate in LC is nearly twice the rate of HC (65% vs. 34%). However, this is already captured by the game-theoretic predictions.

While the degree of unraveling is crucially dependent on the cost of revelation, the degree of equilibrium-consistency appears to be rather independent of this cost. In Low Cost and in High Cost, up to 100% of all revelation decisions are in line with the theoretic predictions. In the final period, about 90% of all decisions correspond to the equilibrium actions. Increasing the cost of revelation does not, therefore, reduce the degree of equilibrium consistency. There are generally only few types who manage to conceal their type when the equilibrium calls for revelation. Altogether, the equilibrium predictions appear to impose an upper bound on the degree of unraveling that will actually be observed—an upper bound that is hardly missed in most cases.

The policy implications we can derive from our results are as follows. Since unraveling will be substantial, voluntary disclosure of personal information does constitute a severe threat to privacy. The ex-ante uninformed parties are able to use the information to their benefit, even though they should not be able to do so in the context of our game. As a consequence, firms are likely to spend considerable efforts and resources on the acquisition of more and more information by nudging people into disclosing more and more details about themselves.

Especially in the labor market, where the bargaining power is usually asymmetric and the data to be disclosed is particularly sensitive, unraveling may cause substantial welfare losses. Hence, we agree with Peppet (2011) in that further regulation may be required.

4.A Additional tables

Market A

Worker	Productivity	No Employers Pred.	No Employers Data	High Cost Pred.	High Cost Data	Low Cost Pred.	Low Cost Data
1	200	0	0.02	0	0.00	0	0.06
2	210	0	0.07	0	0.00	1	0.22
3	230	0	0.03	0	0.06	1	0.11
4	260	0	0.07	0	0.00	1	0.61
5	300	0	0.10	0	0.11	1	0.89
6	600	1	0.82	1	1.00	1	1.00

Market B

Worker	Productivity	No Employers Pred.	No Employers Data	High Cost Pred.	High Cost Data	Low Cost Pred.	Low Cost Data
1	200	0	0.13	0	0.00	0	0.11
2	448	1	0.33	1	0.22	1	0.72
3	510	1	0.40	1	0.06	1	0.94
4	551	1	0.65	1	0.56	1	1.00
5	582	1	0.83	1	0.83	1	1.00
6	607	1	0.82	1	1.00	1	1.00

Market C

Worker	Productivity	No Employers Pred.	No Employers Data	High Cost Pred.	High Cost Data	Low Cost Pred.	Low Cost Data
1	200	0	0.05	0	0.00	0	0.11
2	280	0	0.03	0	0.00	1	0.22
3	360	0	0.12	0	0.06	1	0.72
4	440	1	0.38	1	0.44	1	1.00
5	520	1	0.77	1	0.78	1	1.00
6	600	1	0.82	1	1.00	1	1.00

Table 4.3: Workers' decisions dependent on workers' types.

4.B Instructions

Part 1 - Holt Laury
Welcome to this experiment on decision making!

The experiment is separated into two parts. These instructions only cover the first part. You will get the instructions for the second part after the first part has finished. No personal data will be saved in the context of this experiment.

In the first part of the experiment you have to decide ten times between two lotteries. There is always an “Option A” and an “Option B”. The exact lotteries are described in the screenshot below.

No.	Option A	Decision	Option B
1.	EUR 2.00 with a probability of 10% or EUR 1.60 with a probability of 90%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 10% or EUR 0.10 with a probability of 90%.
2.	EUR 2.00 with a probability of 20% or EUR 1.60 with a probability of 80%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 20% or EUR 0.10 with a probability of 80%.
3.	EUR 2.00 with a probability of 30% or EUR 1.60 with a probability of 70%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 30% or EUR 0.10 with a probability of 70%.
4.	EUR 2.00 with a probability of 40% or EUR 1.60 with a probability of 60%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 40% or EUR 0.10 with a probability of 60%.
5.	EUR 2.00 with a probability of 50% or EUR 1.60 with a probability of 50%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 50% or EUR 0.10 with a probability of 50%.
6.	EUR 2.00 with a probability of 60% or EUR 1.60 with a probability of 40%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 60% or EUR 0.10 with a probability of 40%.
7.	EUR 2.00 with a probability of 70% or EUR 1.60 with a probability of 30%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 70% or EUR 0.10 with a probability of 30%.
8.	EUR 2.00 with a probability of 80% or EUR 1.60 with a probability of 20%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 80% or EUR 0.10 with a probability of 20%.
9.	EUR 2.00 with a probability of 90% or EUR 1.60 with a probability of 10%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 90% or EUR 0.10 with a probability of 10%.
10.	EUR 2.00 with a probability of 100% or EUR 1.60 with a probability of 0%.	Option A ○ ○ Option B	EUR 3.85 with a probability of 100% or EUR 0.10 with a probability of 0%.

Continue

After you have made the ten decisions, the first part is completed. At the very end of the experiment, i.e., after the second part of the experiment has finished, the computer will randomly pick one of the ten lotteries that will be paid. You can document your decisions on the screenshot if you want to compare your decisions to the results once they are displayed.

At the end of the experiment the computer will generate two independent random numbers which are both equally distributed on the interval [0; 1]. If the first random number is between 0.00 and 0.10, number 1 will be paid, if it is between

0.10 and 0.20, number 2 will be paid, and so on. If the first random number is between 0.90 and 1.00, number 10 will be paid.

The second random number decides whether you have won the higher or the lower amount of money. For example at number 3 you earn the higher amount if the second random number is smaller than 0.30. Otherwise you will get the lower amount of money. At the number 8 the second random number needs to be smaller than 0.80 to get the higher amount of money.

Control questions
Assume your decisions were as follows:

No.	**Choice**
1	A
2	A
3	A
5	B
6	B
7	B
8	B
9	B
10	B

1. Assume the first random number is 0.2748 and the second one is 0.4711. Which number will be paid in this case and which amount would you have gained?

2. Suppose the first random number is 0.8456 and the second one is 0.7123. Which number would be paid in this case and which amount would you have gained?

Part 2 - Revelation game
First, please read these instructions carefully. This experiment is anonymous. That means you will not get to know which participants you have interacted with or which participants acted in which roles during the experiment. Please be aware that you are not allowed to talk to other participants during the experiment. If you have any questions please raise your hand and we will come to your cubicle and answer your question personally.

In this experiment the participants will act as workers and as employers. At the beginning of the experiment the computer randomly determines the role you will play. The assignment remains constant for the duration of the experiment.

In total, there are 18 periods in this experiment. In each period of the experiment the computer will randomly sort workers and employers into groups. One group always comprises one worker and two employers. This sorting will take place in each period. Hence, you will not be interacting with the same participants in every period.

The workers in this experiment differ with regard to their productivity. The productivity of the worker determines the revenue of the employer who hires the worker. An employer who hires a worker with a productivity of 200 earns 200 ECU. From this revenue the employer has to pay a wage to the worker, but this will be explained at a later stage.

Moreover, there are three different labor markets which are played on a rotating basis: Market A, Market B and Market C. At the beginning of each period your screen will display the labor market to be played in the corresponding period. The labor markets differ in the possible productivities of the workers.

	Labor market A	**Labor market B**	**Labor market C**
Possibility 1	200	200	200
Possibility 2	210	448	280
Possibility 3	230	510	360
Possibility 4	260	551	440
Possibility 5	300	582	520
Possibility 6	600	607	600
Average	300	483	400

Productivities in the three labor markets.

In the table you can see the different labor markets in the experiment. Assume Labor Market B is played in this period. As a consequence, in this period a worker can have either of the following productivities of 200, 448, 510, 551, 582 or 607. All six possible productivities are equally likely. The computer will randomly determine the productivities of the workers in this period by making a random draw from this set. Note that in all periods, each possible productivity will be attributed to exactly one worker.

Every participant will begin the experiment with a starting capital of 1600 ECU. This starting capital simultaneously serves as the show-up fee, which is the amount of money you receive independent of behavior during the experiment, just for arriving at the lab on time.

Your task:
Each period has three stages where decisions need to be made: In the first stage workers have to decide, then the employers need to make a decision and finally workers need to decide again. At the end of a period everybody receives a summary of the outcome of that period.

First decision of the workers: certificate

In the beginning workers get to know their productivities. The employers do NOT, however, get to know the productivities of the workers, they just know which labor market (A, B, C) is being played in that period.

Each worker has to make the following decision in every period of the experiment: she needs to decide whether or not she would like to buy a certificate at a price of 100 ECU. The certificate reveals your productivity. That means if you decide to purchase the certificate the employers will get to know your productivity in this period. If you do not buy a certificate, the employers only know which labor market is being played in this period and thus only know the six possible values your productivity can take this round. If you decide to buy the certificate you will have to pay the price of 100 ECU from the wage paid to you by one of the employers.

Decision of the employer: Making a wage offer
As an employer you receive an endowment of 200 ECU each period. Beyond that you have to make a wage offer to the worker in your group. If worker bought the certificate for 100 ECU you will get to know her productivity in this period. If the worker did not buy the certificate you only know the six possible values the productivity can have in this period. Your wage offer needs to be at least 0 ECU and at most 800 ECU. Note that wage offers may comprise up to two decimal places.

Second decision of the worker: accepting a wage offer
In the third stage the workers get to know the wage offers they received from the two employers in their group and have to accept either of the two offers. The employer, whose wage offer is accepted, will hire the worker. She receives the productivity of the worker as a revenue but also has to pay the wage she offered to the worker. The other employer does not hire the worker. She does not get a revenue and does not have to pay a wage. The worker receives the offer she accepted as wage payment. Depending on whether or not she has bought the certificate, she may still have to pay the costs of the certificate (100 ECU). Table 2 summarizes this profit calculation.

Worker without certificate	Worker with certificate	Employer whose bid is accepted	Employer whose bid bid is not accepted
Wage	Wage – 100 ECU	200 + Productivity – Wage	200

Table 2: Profit calculation

Example:
Consider the following example. A worker and employers 1 and 2 form a group. The worker has a productivity of 300, the wage offer of the employer 1 is 240 ECU

and the wage offer of the employer 2 is 250 ECU. Assume the worker accepts the wage offer of the second employer.

In this case Employer 1 earns only the basic amount of 200 ECU in this period. The worker earns 150 ECU (250 ECU wage minus 100 ECU certificate) in case she bought the certificate and 250 ECU otherwise. The second employer earns in this period:

+ 200 ECU (base payment)
+ 300 ECU (productivity of the worker)
− 250 ECU (wage of the worker)
= 250 ECU

As previously mentioned, the experiment lasts 18 periods. At the end, the earnings you have gained during the experiment will be converted into EUR at a rate of 400 ECU = 1 EUR and you will receive the corresponding amount in cash. Furthermore we will round up the amounts to the next 50-cent threshold. Please be aware that the displayed amount paid out includes the show-up-fee which was integrated into the starting capital.

We kindly ask you to wait in your cubicle until we call you to get your payment. Please ensure you bring all the documents you have received from us when you collect your payment.

If you have any questions, please raise your hand now!

Control Questions
Assume that Labor Market B is played this period.

1. What is the probability that the worker in a group has a productivity of 582?
2. What is the probability that the worker in a group has a productivity of 448?
3. What is the probability that the worker in a group has a productivity of 360?

Assume that the worker in your group has a productivity of 510.

1. What does the worker earn in this round when the accepted wage offer is 450 and she has not bought a certificate?

2. Was does the worker earn in this round when the accepted wage offer is 450 and she has bought a certificate?

3. What do the employers 1 and 2 earn, if the wage offer is 300 ECU (employer 1) or 350 ECU (employer 2) and the worker chose to accept the wage offer of employer 1?

What information does the employer in a group have about the productivity of the worker if he has bought a certificate?

What information does the employer in a group have about the productivity of the worker if he has not bought a certificate?

How much is the certificate for the worker?
How much is a certificate for the employer who hires the worker?
How much is a certificate for the employer who does not hire the worker?

Chapter 5

Depth of Reasoning in the Market for Lemons: A Note on the Distribution of k-Levels

Co-authored with Hans-Theo Normann and with Dorothea Kübler

5.1 Introduction

The level-k model is a work-horse in behavioral economics. It allows players to have various depths of reasoning. A level-k player believes all other players are of level-(k-1) and best-responds accordingly. The model was introduced by Nagel (1995) and Stahl and Wilson (1995) and has triggered various extensions and refinements such as the model of noisy introspection by Goeree and Holt (2004) or Camerer et al.'s (2004) model of cognitive hierarchies.

In a recent paper, Arad and Rubinstein (2012) (henceforth called A&R) introduce the "11-20 money request game", specifically designed to elicit empirical distributions of k-levels. Two players simultaneously request an amount of money (measured in integer Shekel) from the set $\{11, 12, ..., 20\}$. Each player receives the amount requested plus an additional 20 Shekel if the own request is exactly one Shekel lower than the other player's request. If $k = 0$ players choose 20, any choice $20 - x$ exactly corresponds to a k-level of x.

A&R convincingly argue that their game is particularly suitable for studying level-k reasoning and list a total of six arguments in favor of their model. Among the arguments why the model is nicely suitable for level-k elicitation are one, incentives in their game are not confounded by social preferences; two, the (desirable) non-existence of pure-strategy Nash equilibria and, three, the absence of dominated strategies in their game.

In this paper, we present another experimental game suitable for the elicitation of k-levels which, however, violates several of the aforementioned arguments in favor of the money-request game. We study a labor market where workers can choose to reveal their productivity at a cost. In our main variant, only the worker with the highest productivity will reveal when $k = 1$; the worker with the second highest productivity will reveal when $k = 2$ and so on. Generally, lower productivity workers will reveal only for higher k-levels. For $k \geq 5$ and in Nash equilibrium, there is complete unraveling. Rational revelation imposes a negative externality on others, so social preferences might have an impact. Further, there is a unique pure-strategy equilibrium and one player has a dominated action in our game.

Our results confirm A&R in a double sense. We find that social preferences may indeed confound level-k elicitation, but, when isolating this effect, we observe practically the same distribution of k-levels as A&R. In about 20 percent of the cases, participants choose not to reveal for *all* productivity levels. Within the level-k model, this behavior would be classified as $k = 0$. However, this strategy is unlikely to be the result of random or uninformed behavior; rather it is consistent with other-regarding preferences including inequality aversion (Fehr and Schmidt, 1999) and surplus maximization (Engelmann and Strobel, 2004). When we exclude these choices as outside the level-k model, our distribution of k-levels is practically identical to the one found in A&R. In turn, this suggests that other possible confounds A&R mention (unique pure-strategy equilibrium, dominated actions) are of less importance.

5.2 The game

There are six workers with productivities $\theta_1 \leq \theta_2 \leq ... \leq \theta_6$. Workers simultaneously choose whether to *reveal* or to *conceal* their productivity. Let $I_i \in \{0, 1\}$ indicate whether worker i has chosen to reveal her productivity, with $I_i = 1$ denoting revelation. With $c > 0$ being the cost of revelation, formally, worker i's payoff is

$$\Pi_i = \begin{cases} \theta_i - c & \text{if } I_i = 1 \ \ (\textit{reveal}) \\ \sum_{j=1}^{n}(1 - I_j)\theta_j / \sum_{j=1}^{n}(1 - I_j) & \text{if } I_i = 0 \ \ (\textit{conceal}). \end{cases}$$

In words, if worker i chooses to reveal, i earns her productivity minus the revelation cost. If not, she receives the average productivity of all workers who have chosen not to reveal.

The Nash equilibria of this game depend on the productivities and c. It is straightforward to see that concealing is a dominant action for worker 1. For $c = 0$, all workers except for the worker with productivity θ_1 will reveal. Multiple pure equilibria and mixed equilibria may exist.

5.3 Experimental design and procedures

We use three different variants in the experiments, called *Market A*, *Market B* and *Market C*. Each market represents different worker productivities but we employ $c = 100$ throughout. The productivities and the unique Nash equilibrium for each market are summarized in Table 5.1.

Worker productivity	Market A	Market B	Market C
θ_1	$200^{k\geq1}$	$200^{k\geq1}$	$200^{k\geq1}$
θ_2	$210^{k\geq1}$	$\mathbf{448^{k\geq5}}$	$280^{k\geq1}$
θ_3	$230^{k\geq1}$	$\mathbf{510^{k\geq4}}$	$360^{k\geq1}$
θ_4	$260^{k\geq1}$	$\mathbf{551^{k\geq3}}$	$\mathbf{440^{k\geq3}}$
θ_5	$300^{k\geq1}$	$\mathbf{582^{k\geq2}}$	$\mathbf{520^{k\geq2}}$
θ_6	$\mathbf{600^{k\geq1}}$	$\mathbf{607^{k\geq1}}$	$\mathbf{600^{k\geq1}}$

Table 5.1: Minimum k-level required such that a worker's action is equal to her equilibrium action. Entries in bold face indicate that a worker reveals in Nash equilibrium.

Table 5.1 shows which level of reasoning is required for equilibrium play. To begin with, we assume that $k = 0$ players randomize between revealing and concealing, both equally likely. Table 5.1 indicates that the workers with the highest productivity reveal when $k \geq 1$. Workers who conceal in equilibrium play their equilibrium action for any $k \geq 1$; by contrast, revealing may require higher levels of reasoning.

The three markets are played on a rotating basis. Subjects begin with Market A, then turn to Market B in the second period and Market C in the third period before they start all over with Market A in period four. In total subjects play 15 rounds, five repetitions of each market.

Our main variant is Market B because it is suitable to elicit k-levels up to $k = 5$. Markets A and C are motivated as control treatments to Market B. Their primary purpose of these markets is to confirm that the share of subjects reasoning at some level is constant in absence of more demanding decisions.

Subjects play the game as outlined in Section 5.2. In order to determine subjects' k-levels, we use the strategy-elicitation method and have our participants make as-if decisions conditional for each of the six workers.[1] Once all subjects have decided, a random computer draw determines which subject acts in the role of which worker and subjects are presented with a summary of the results. The

[1] If we asked subjects for an actual decision of just one specific worker, the data would be inconclusive regarding the k-level. Consider as an example worker 4 in Market B: if she conceals, this implies $k < 3$; if she reveals, we learn $k \geq 3$; an exact k-level cannot be concluded. Using the strategy method, the subject's switching point yields an exact k-level (at least up to $k = 5$): if, in Market B, a subject conceals as worker 1 to 3 and reveals as worker 4 to 6, we know this participants reasons at level $k = 3$.

feedback contains information about the realization of the random draw, the corresponding decision of the subject, the payment to subjects who have not revealed their productivity and the payment to the subject. The feedback did not contain specific information on the decisions of the other participants.

We had 66 subjects participating in the experiment. This results in eleven independent observations when counting one group of six participants as one independent observation. The experiment was conducted at the lab of the *Technical University Berlin* in January 2012. A session lasted approximately 90 minutes and subjects earned 10.99 EUR on average. The experiments were conducted using Fischbacher's (2007) z-Tree software. The ORSEE tool (Greiner, 2004) was used for on-line recruitment.

5.4 Results

5.4.1 Choices

Figure 5.1 displays the aggregate distribution of choices from of our main variant, Market B. Out of the $2^6 = 64$ possible strategies, six strategies are chosen frequently: there are five monotonic strategies (with a unique switching point from conceal to reveal for some higher productivity) that are consistent with level-k thinking.[2] Another frequent strategy has the player conceal for all productivities, is labeled "Conceal" in the figure. The remaining 58 strategies are rarely chosen. They include all non-monotonic strategies which are level-0 behavior as they can be considered as the result of players picking arbitrary strategies. There are also further monotonic strategies where a player reveals "too much" from a level-k perspective, also included under level-0. In Figure 5.1, choices from all periods labeled Level-0 to Level 5 and Conceal, accordingly.

The strategy where subjects choose to conceal for any productivity (Conceal) is challenging. From a level-k perspective, such choices should be considered level-0 play. However, it appears unlikely that this behavior is the result of randomization or uninformed behavior. The reasons for the popularity of this particular strategy are probably found outside the level-k model. Note that the strategy maximizes joint payoffs and implies the only outcome where all players earn the same payoffs,[3, 4] It seems inappropriate to categorize this strategy as level-0. Since we cannot interpret it within the level-k model otherwise, we drop the Conceal decisions the further analysis.

[2] Note that the level-5 strategy not only coincides with the Nash equilibrium, it also captures the choices by all players reasoning at higher levels.

[3] See Chapter 3 for more details on inequality aversion in this context.

[4] It is also consistent with privacy concerns. In Chapter 3, we analyze the same game without using the strategy method and point out that privacy concerns may prevent subjects from revealing their productivity, as suggested by a comparison to an additional neutrally framed treatment they employ.

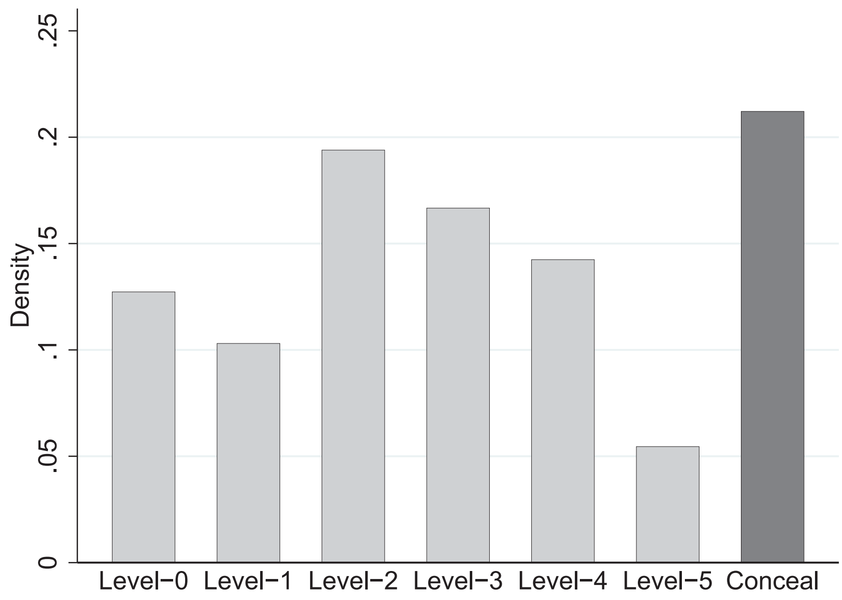


Figure 5.1: Distribution of k-levels Market B (all periods).

5.4.2 Level-k identification

In contrast to A&R, our data needs to be adjusted in order to obtain the underlying distribution of k-levels. This is due to differences concerning the assumptions for level-0 play. We follow the literature in that we assume level-0 players to randomize over their entire action set. Hence, it may occur that level-0 players accidentally pick one of the five strategies that are associated with higher k-levels. There are 64 strategies, 58 of which can only be explained by level-0 play. Since level-0 players are assumed to randomize over all strategies, the share of level-0 decisions should equal $\frac{64}{58}$ times the density of choices that directly qualify as level-0. The density of the other choices can then be derived by distributing the remaining mass according to the frequencies observed.

Table 5.2 summarizes this conversion for the data of Market B (all periods). The row "density choices" is underlying figure 5.1. The row "density adjusted" shows the implication of the aforementioned adjustment procedure. We note that not much changes. Finally, the row "density level-k normalizes the sum level-k choices to 1 when we purge the Conceal choices from the data.

5.4.3 Main results

Figure 5.2 illustrates our main result. It reports the cumulative density function of the k-levels observed in A&R's "Basic" and periods one and five of our Market B. There are virtually no differences between the A&R's and our distributions. A minor discrepancy is that we have somewhat more mass on $k = 0$. In any

	$k = 0$	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k \geq 5$	conceal
Freqency choices	42	34	64	55	47	18	70
Density choices	0.127	0.103	0.194	0.167	0.142	0.055	0.212
Density adj.	0.140	0.101	0.191	0.164	0.140	0.054	0.209
Density level-k	0.178	0.128	0.241	0.208	0.177	0.068	–

Table 5.2: Conversion results.

event, a Kolmogorov-Smirnov test ($D = 0.129$) reveals that we cannot reject the null hypothesis that the samples from Market B (first period) and A&R's Basic are drawn from the same distribution at any conventional significance level (the threshold for $p = 0.1$ would be $D = 0.202$).

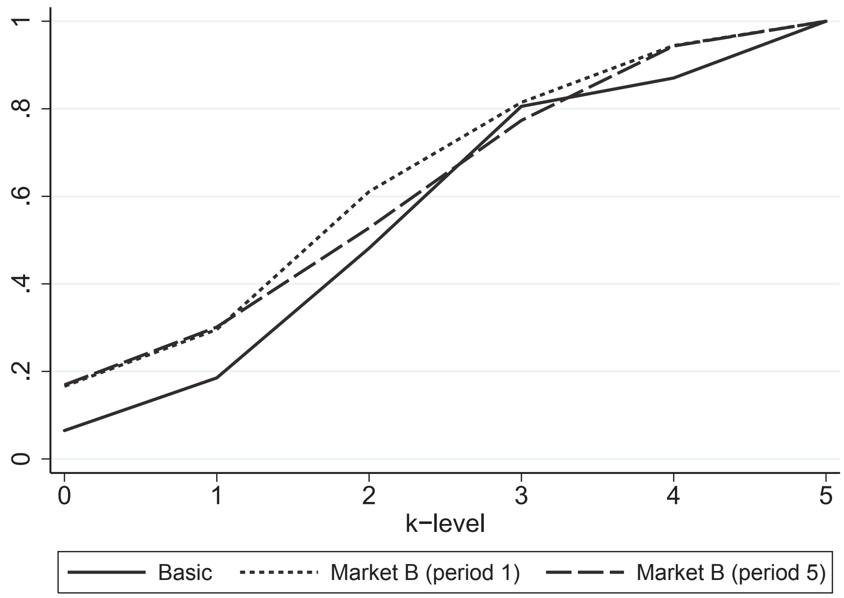


Figure 5.2: Arad and Rubinstein's Basic vs. Market B (first period) and Market B (period 5 or last period).

A second result is that learning is rather limited in our game. The results from period one and period five of Market B do not differ much. To formally test this, we conduct a Wilcoxon signed-rank test using group mean and median k-levels. We find that neither test is significant ($p = 0.464$ and $p = 0.344$, two-tailed, for mean and median, respectively). This is somewhat surprising given subjects can gain experience in four rounds playing Market B. In guessing games, subjects quickly learn to play the equilibrium after three to four repetitions.

5.4.4 Markets A and C and A&R's other variants

Markets A and C serve as control treatments to Market B. Will behavior change when fewer steps of reasoning are required for equilibrium play, that is, when there are no more demanding cases? The data from our controls is generally consistent with the data from our main treatment. For instance, the share of subjects reasoning at a level $k \geq 1$ is remarkably stable across markets. We find that there is no significant difference concerning this share between the first period of Market B and Market A or Market C (Friedman test, $p = 0.529$). Market C has a high share of level-2 players, though, also compared to A&R.

	Arad and Rubinstein			This study		
	Basic	Cycle	Costless	Market A	Market B	Market C
Level-0	0.065	0.125	0.151	0.185	0.178	0.200
Level-1	0.120	0.472	0.396	0.815*	0.128	0.160
Level-2	0.296	0.222	0.208		0.241	0.477
Level-3	0.324	0.097	0.094		0.208	0.164*
Level-4	0.065	0.042	0.038		0.177	
Level ≥ 5	0.130*	0.042*	0.113*		0.068*	
Level $k \geq 1$	0.935	0.875	0.849	0.815	0.822	0.800

Table 5.3: Comparisons of k-levels elicited in this study and in Arad and Rubinstein (2012). Entries in bold face indicate that the values also comprise any higher k-level. Entries marked with * also comprise the choices of all higher levels.

A&R also conduct other variants as robustness checks. The "Cycle" variant is identical to "Basic" (described in the introduction) except that a player choosing 20 will receive the bonus if the other player chooses 11. The only difference between "Costless" and "Basic" is that all players who do not choose 20 will receive a risk-free payoff of 17 instead of the number they choose. Players will still receive the bonus if they choose a number that is one less than the number chosen by the other player. Compared to "Basic", "Cycle" and "Costless" have a substantial mass on level-1 players. Comparing A&R to our Market B, we note that the discrepancies between their three variants are at least at substantial as the difference Market B, even if we included the "unconditional concealment" players.

5.5 Conclusion

Our experiments, like those of Arad and Rubinstein (2012), aim at deriving a distribution of players depths of reasoning for the level-k model, introduced by Nagel (1995) and Stahl and Wilson (1995). Such empirical results are essential to make predictions for other games.

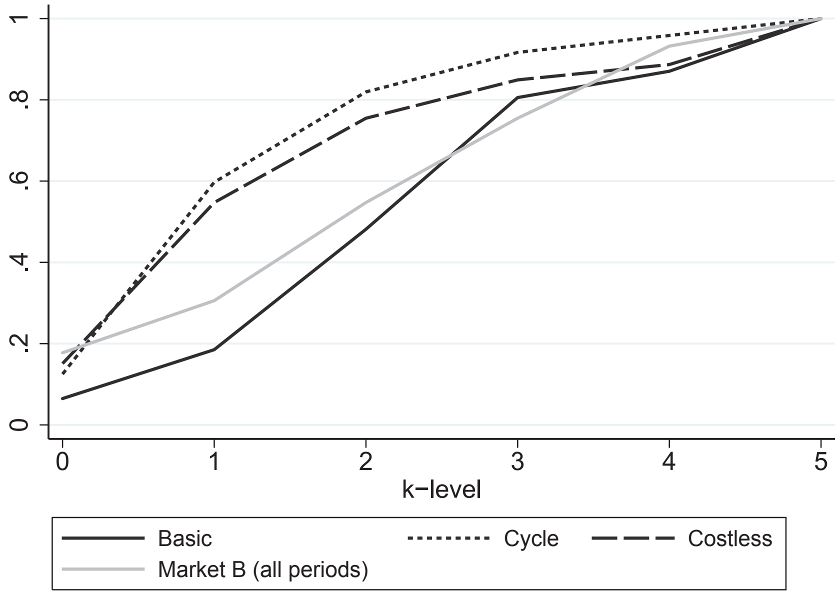


Figure 5.3: All A&R treatments vs. first and last period of Market B

Even though our game differs quite substantially from the money request game of Arad and Rubinstein (2012), we observe practically the same distribution of k levels once we exclude a sizable share of choices where players conceal for any productivity. Rather than categorizing these choices as $k = 0$, we believe such behavior may result from other-regarding preferences. If so, these conceal decisions are outside the level-k model and should hence be dropped from the analysis. The remaining distribution of k-levels in our main variant is practically identical to the distribution in Arad and Rubinstein (2012).

5.A Instructions

Welcome to this experiment on economic decision making.

Please read these instructions carefully. The experiment is conducted anonymously, that is, you will not get to know which of the other participants interacted with you or which participant acted in which role. Please note that now that the experiment has started, you must not talk to other participants. If you have any questions, please raise your hand and we will come to you.

In this experiment all participants act as workers. The workers in this experiment differ with respect to their state of health. The state of health of a worker determines his or her productivity and hence also the revenue of a fictional employer (played by the computer). Furthermore, there are in total three different labor markets, which are played on a rotating basis: labor market A, labor market B and labor market C. At the beginning of each period, you will see a screen showing which market is being played in that period. There are six different workers with different states of health.

	Labor Market A	Labor Market B	Labor Market C
Worker 1	200	200	200
Worker 2	210	448	280
Worker 3	230	510	360
Worker 4	260	551	440
Worker 5	300	582	520
Worker 6	600	607	600
Average	300	483	400

Table 1: State of health of the workers 1-6 in the three labor markets.

In the table above you can see the different workers of this experiment and their state of health. Suppose market B is being played in this period. If the fictional employer (who is played by the computer) is hiring, for example, worker 3, then worker 3 will create a revenue of 510 points for the employer. Worker 1 will create a revenue of 200 points due to worse health. In a period where market C is being played the workers 1 and 3 create revenues of 200 (worker 1) or 360 points (worker 3). The state of health of any worker is of course completely fictional and is determined randomly by the computer.

The experiment lasts for 15 periods. At the beginning of each period the current market will be displayed on your monitor. In each period you need to make a decision for all six workers. Once all participants have made their six decision, it will be randomly determined which of these six decisions is relevant for your payment in this period. That means, at the beginning of the experiment you will be randomly sorted in groups of six participants. Once all members of a group have made their six decions the computer will randomly determine which group member represent which worker in that period. This will be the worker whose payoff you receive in that period. Even though you decide for all six workers, at the end of the period you will only receive a wage payment of a randomly chosen worker. This random draw will be such that there is always exactly one worker 1, one worker 2, one worker 3 and so on in each group. In other words, in each group there is always exactly one worker of either health condition. As mentioned before, at the beginning of each period you will get to know from your monitor, which of the three labor markets (A, B or C) is played in this period.

Your task in the experiment:

In each period all participants need to make the following decision for every worker. You can choose whether the worker should buy a health certificate for a fee of 100 ECU. The health certificate reveals the worker's health condition and affects her payment in that period as follows:

1. If a worker purchases a health certificate, her payment will correspond to her health condition minus the fee of 100 ECU.

2. If a worker does not purchase a health certificate, her payment will correspond to the average health condition of all workers who do not have a health certificate.

All participants make their decisions independently. That means that they do not know whether or not the other participants purchase any certificates. Moreover, at the time of your decision you will unaware of the resulting market wage. You will not get this information until the very end of the period.

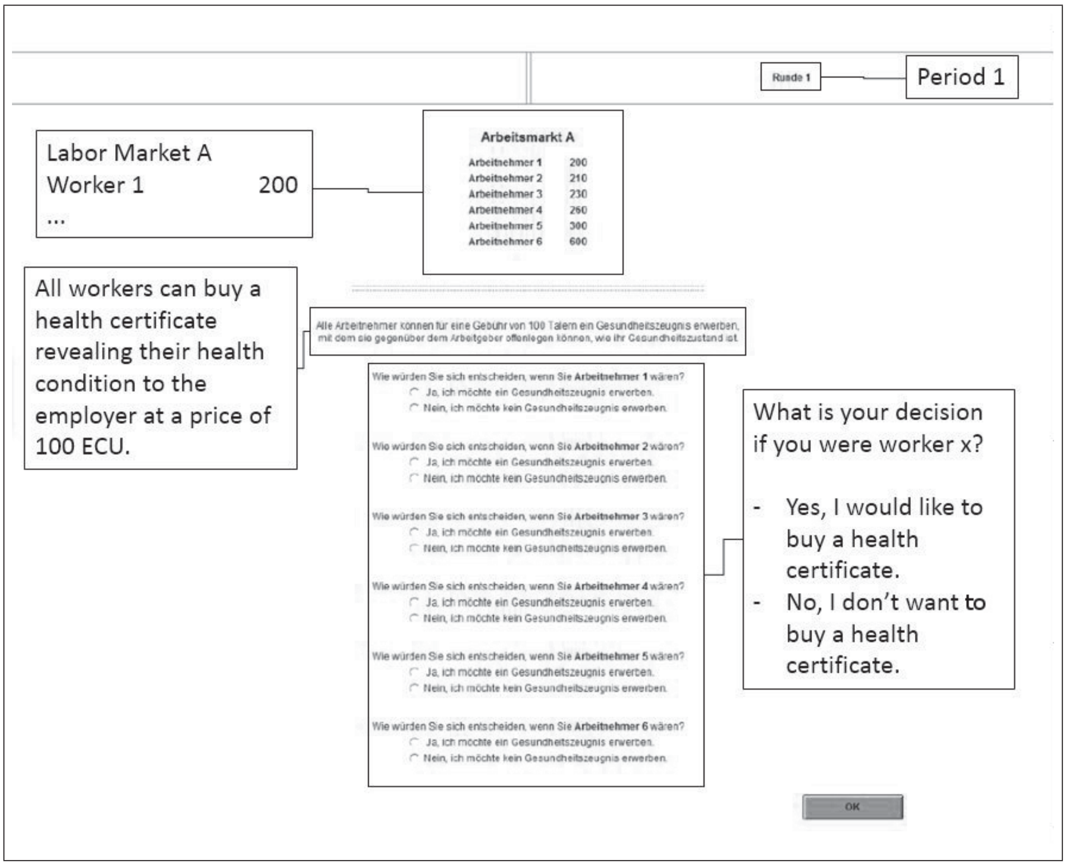
Once all workers have reached their decisions you will get detailed information about the result of this period on your monitor. The next period begins as soon as all participants have read the summary and clicked on "Continue". Below you find an example of the decision screen for Market A.

An example: Suppose labor market B is played in this period. At the beginning, when no worker has revealed his health yet, the average health of all workers without health certificate is:

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

The market wage equals 483 ECU in this case. Now each participant decides in the role of the single workers, whether he wants to reveal the respective health or not. In the table above you can also see the average health conditions for the markets A and C. Once all participants have made their decision, all will receive detailed information on the result.

Assume that the participants in the role of worker 3 and 5 in this period have decided to reveal the health conditions of those workers. In this case worker 3 receives a wage payment of 510 ECU and worker 5 receives a wage payment of



582 ECU. Both have revealed their health, hence both have to pay the fee of 100 ECU. Thus, the participant in the role of worker 3 earns 510 ECU – 100 ECU= 410 ECU and the participant in the role of worker 5 earns 482 ECU. Suppose the other participants have decided, that the remaining workers (1, 2, 4 and 6) shall not get a health certificate. In this case no fee has to be paid and the workers receive the market wage as wage payment. In this case the average health of all workers without health certificate will be: $\frac{200+448+551+607}{4} = \frac{1806}{4} = 451.5$ ECU. This is the market wage the participants in the role of the workers 1, 2, 4 and 6 will receive. Note that it is not possible that you have to more than one fee per period. For instance, if you decide that four different workers should get a health certificate in a period, there will still only be one worker that will determine your payoff and you have to pay for one health certificate if any. No fees will be charged for the other three health certificates since the corresponding decisions will remain payoff-irrelevant in that period. Even though you have to make a decision for all six workers, you will only be paid for one decision. However, you will not get to know the payoff relevant worker and the market wage until you have made all your decision.

As already mentioned, the experiment will take 15 periods in total. At the end, your earnings will be converted into Euro at a rate of: 500 ECU = 1 Euro. Furthermore we will round up the payoffs to the next 50-cent-amount. Please wait inside your cubicle until we call you for collecting your payment. After the experiment, please bring also all the documents you received from us.

If you have any further questions, please raise your hand now!

Chapter 6

Conclusion

In this thesis, we presented four papers analyzing the economics of privacy.

Chapter 2 analyzes *"The Willingness to Sell personal Data"*. In a controlled laboratory experiment, we elicit the minimum price subjects request such that they agree to have their personal data used commercially. The results are not unambiguous. On the one hand, we find that many subjects exaggerate their privacy concerns. In non-incentivized surveys, a large majority of those questioned will typically deny any willingness to disclose personal data. However, our experiments document that roughly five in six subjects sell their personal data for commercial uses at prices as low as €5. On the other hand, our experiments show that there is a minority who will persistently refuse to provide any personal data. These subjects do not fall for incidental requests such as our TIOLI offers and they waive up to €50 in our BDM design. Hence, about one in six participants is highly concerned about privacy issues.

In the chapters three and four we addressed the so-called unraveling problem. Unraveling of privacy may occur if some agents have an incentive to disclose a given information while others do not have such an incentive. In this case, an enquirer may conclude that an agent who refused to disclose her information did not have an incentive to provide it. Hence, the refusal to provide personal data may already reveal the information contained in that data.

In Chapter 3, we present a labor market experiment on unraveling where the focus is exclusively on the disclosure behavior of the workers. We find that unraveling is less complete if the information to be disclosed is perceived sensitive. A loaded frame significantly decreases the probability that workers reveal their type. However, there is generally a substantial degree of unraveling, albeit not as substantial as predicted by economic theory. A systematic bias is preventing low-productivity workers from disclosing their private information. This effect appears to be driven by a lack of iterative reasoning—subjects are not always capable of reasoning enough steps to find the own equilibrium action.

In Chapter 4, we extend the research from Chapter 3 by introducing employers and a parameterization where the cost of revelation is negligible. The results from Chapter 3 are robust in both dimensions. Lowering the cost of revelation increases the degree of unraveling. However, this increase is already captured by the theoretical predictions. Introducing employer has an ambiguous effect. On the one hand, workers with a high productivity reveal more frequently because the mere existence of employers reduces the importance of fairness considerations. On the other hand, types with lower productivities reveal less frequently. Employers bid less competitively if the worker reveals compared to the case where the worker conceals. Hence, fewer types of the worker have an incentive to reveal their type.

In Chapter 5 we elicit a distribution of k-levels. We find that the distribution originating from our experiment is virtually identical to a distribution reported by Arad and Rubinstein (2012). This is somewhat surprising since the games used differ quite substantially. It emphasizes our conclusion from Chapter 3: only few people are capable of reasoning at higher levels. If voluntary disclosure of information requires too many steps of iterative reason, a majority will not get to know that they might have an incentive to reveal their type.

By and large, this thesis documents that many people voluntarily disclose personal information if they have a monetary incentive to do so. The share of subjects willing to sell exceeds the share of subjects indicating their consent in non-incentivized surveys quite substantially. However, there is also a minority of about one in six subjects who persistently refuse to provide any information. Our research on unraveling documents that not disclosing certain data may also reveal private information. In our experiments, only few types manage to pool even though they should not be able to do so. Hence, the privacy of subjects who refuse to provide data is just as threatened as is the case for anybody else.

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Appendix

Ich erkläre hiermit an Eides Statt, daß ich die vorliegende Arbeit ohne Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe; die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht.

Düsseldorf, 6. August 2014. Volker Benndorf