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Research Proposal Summer School Revealed Preferences

Revealed Preferences under Framing: User valuation of privacy

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1 Introduction

In stated preference studies people tend to express a high valuation for privacy, yet observed behavior is typically at odds with these stated preferences. This phenomenon has come to be known in the literature as privacy paradox (N. Gerber, P. Gerber, and Volkamer 2018). Some have argued that this observation is merely illusory since an individual can state a high valuation of privacy in general, but in a specific situation, a cost-benefit analysis might lead people to discount privacy concerns (Acquisti, Brandimarte, and Loewenstein 2015, p. 2). This refutation falls short insofar, as it is a well documented result in behavioral economic research that people's decision making capabilities are only in part rational. Especially in situations when people are uncertain about the consequences of their actions, when they are unsure about their preferences, or when they are under time pressure, people often search for clues in their surrounding to provide guidance (Acquisti, Brandimarte, and Loewenstein 2015, p. 3). One possible source of orientation can stem from the specific way in which a decision is framed. Framing effects, in turn, introduce a difficulty when researchers are interested in learning about people's true preferences. Deriving revealed preferences in the presence of framing can be problematic if people's preference is not consistent over the set of framings. Goldin and Reck (2020) propose a new method to identify the fraction of consistent decision makers and to extrapolate from them to the entire population. A decision maker is consistent when her decision is not influenced by the frame. Preferences can then then be recovered even when framing effects are present, as if the whole population was comprised of framing-consistent decision makers.

Their methodology rests on the insight that even though framing-consistent preferences cannot be observed on the *individual level* in typical datasets (i.e in datasets where researchers observe a respondent's answer generated under only one framing), on the *population level*, the fraction of consistent decision-makers can be identified if researchers see answers from all framings. From the subgroup of consistent decision makers their approach extrapolates to the entire population. Their method is described in detail in section 2.

This research proposal suggests to build on the results obtained by Goldin and Reck (2020). It suggests to collect a dataset that can be used to test their method. At the same time, the results from the analysis of this dataset will produce framing-consistent estimates of users' privacy setting preferences. The test of Goldin and Reck (2020)'s method will constitute a methodological contribution to the literature on revealed preferences under framing. The preference estimates will contribute to the literature on privacy preferences and will have implications for policy makers concerned with the question of security of personal data on the internet.

In particular, it is proposed to collect a dataset online recording people's decisions about browser cookie settings via a type of data collection akin to the one in Levy (2020). Levy (2020) wrote a browser add-on for Google's Chrome browser, which tracked in an experiment the participants' visited websites for two weeks. It is proposed to write a similar browser add-on to track people's decision about browser cookie settings. According to the General Data Protection Regulation (GDPR) users who visit a website from within the European Union or the European Economic Area must be asked for their stated consent on storing browser cookies (*General Data Protection Regulation* 2020). For the intents of this research proposal, one can divide browser cookies into two groups. First, there are essential cookies that are necessary to guarantee the website's functionality. Second, there are third-party ad-tracking cookies. A website's host still has a monetary incentive to nudge users to allow for the ad-tracking cookies. This can be done by choosing the default cookie settings.

The dataset collected online will contain repeated observations of the same individual both under an ad-tracking cookie opt-in framing and an ad-tracking cookie opt-out framing. This additional information can be used to overcome a central limitation in many datasets (where individuals are observed only under one frame). The subset of framing-consistent people can therefore be observed on the individual level. Once these individuals are identified, one can again extrapolate to the entire population, as is done in Goldin and Reck (2020)'s method. Finally, the results from the first approach and the second approach can be compared, yielding an empirical test of Goldin and Reck (2020)'s method.

What would ideal results of this research look like? If the proposed research succeeds, it finds whether Goldin and Reck (2020)'s new method generates estimates that are qualitatively similar and quantitatively close to estimates based on repeated observations of the same individual. By doing so, it will produce estimates of people's privacy preferences which are robust with respect to framing. Here two scenarios are conceivable: It will be found that a large proportion or even a majority of users do have a preference for heightened privacy, i.e. a preference against non essential ad-tracking cookies. Alternatively, it could be found that users do have a preference for ad-tracking cookies, e.g. because allowing for this type of cookie increases the relevance of online advertisement. From a policy point of view, the former result could possibly be interpreted to imply that the rules governing cookie default settings would have to be further tightened, such that websites default setting is to only use technically necessary cookies by default. Ad-tracking cookies would then mandatorily be opt-in. Either way, the analysis will allow to examine if there are interesting sources of heterogeneity in the data, potentially revealing previously unknown relationships between users and their privacy attitudes.

The remainder of this research proposal is structured as follows. Section 2.1 will introduce the basic idea and notation of Goldin and Reck (2020)'s method. Section 2.2 will introduce the assumptions that form the basis for their identification strategy. Section 3.1 will describe how and what kind of data is proposed to be collected. Section 3.2 will describe the identification strategy of Goldin and Reck (2020)'s method. Section 4 concludes.

2 Economic Model

The description of this model follows chapter 1 of Goldin and Reck (2020). A fully detailed description of the model can be found there and is beyond the scope of this research proposal. Here, only the main concepts necessary for understanding this proposal are presented.

2.1 Basic model notation

A decision maker i chooses from a binary decision set $\mathbf{S} = \{0, 1\}$ and two possible frames $D_i \in \{0, 1\}$. In the context of this research proposal, the decision coded with a 0 could refer to an individual's decision to accept only technically necessary cookies and the decision coded with a 1 could refer to an individual's decision to allow for non technically necessary cookies. Frame 0 could be the situation where the default setting is such that technically necessary cookies are the only pre-chosen ones and the user would have to actively engage in clicking on all non-technically necessary cookies she wishes to allow. Frame 1 could then refer to the situation where in the default setting both types of cookies are pre-chosen and the user accepts both types with one click. We can adapt a notation that is akin to what many researchers like to use in a potential outcome setting. $Y_i(0)$ and $Y_i(0)$ denotes then the decision individual i makes under frame $D_i = 0$ and $D_i = 1$, respectively. Decision makers are assumed to have strict ordinal preferences over the set of available options. $Y_i^* \in \{0, 1\}$ denotes the most preferred option. Each decision maker is characterized by a vector of random variables $(Y_i(0), Y_i(1), D_i, Y_i^*)$, which are drawn from an underlying population distribution. For each i, the researcher observes the pair (Y_i, D_i), where $Y_i = Y_i(0)D_i + Y_i(1)(1 - D_i)$. Goldin and Reck (2020) assume for their model that the researcher does not observe Y_i^* and only observes one of $Y_i(0)$ and $Y_i(1)$, depending on the frame D_i.

The data that is suggested to be collected in this proposal deviates in a crucial way from this assumption. In contrast to the datasets Goldin and Reck (2020) have in mind, the dataset in this proposal will contain *repeated* observations of the same individual. The number of observations for each i can be denoted with a subscript $k \in \{1, \ldots, K\}$ such that $Y_{i,k}$ is observed. Importantly, here it is assumed that K is sufficiently large to allow for at least one observation of each framing $D_i \in \{0, 1\}$.

The mean choices among decision makers assigned to a frame is denoted by $\bar{Y}(1) \equiv E[Y_i|D_i = 1]$ and $\bar{Y}(0) \equiv E[Y_i|D_i = 0]$.

Goldin and Reck (2020) continue their description of the model as follows: Each decision maker can choose either consistently, i.e. the same choice under each frame, or choose in a way that is responsive to the frame. Consistency is denoted by $C_i = 1$ iff $Y_i(0) = Y_i(1)$ else $C_i = 0$. Again, they assume that each i is observed only under one frame, such that C_i is not observed. In the context of this proposal, as described above, it is assumed that each i is observed under both frames, such that C_i is identified. This difference is crucial for one of the main contributions of this proposal. The additional information in this dataset allows to calculate two sets of results. For the first one, the additional information in this dataset is not used. The analysis will proceed under the assumption of Goldin and Reck (2020). The second set of results will be obtained using the full amount of information in the dataset. As such, the "ground-truth" that remains hidden under Goldin and Reck (2020)'s assumptions, is observed. In other words, with the dataset proposed here, it will be able to identify all individuals who make consistent choices, independent of the frame. Having these two sets of results, one can compare the estimates from both to arrive at an assessment of the quality of Goldin and Reck (2020)'s model accuracy.

2.2 Model assumptions

One of Goldin and Reck (2020)'s main contributions is to make the necessary assumptions for their analysis explicit. Furthermore, the assumptions are fundamental to their approach and will be required in section 3 to derive framing-consistent estimates for the entire population. For these reasons, the assumptions will be presented shortly here as well. Each assumption is first presented in the way Goldin and Reck (2020) lay them out and subsequently followed by a comment on how each assumption relates to the approach suggested in this research proposal.

- Assumption A1) *Frame separability*: For all i, Y_i^* does not depend on D.

For each individual, the most preferred option does not depend on the framing. This is an assumption about the content of a decision makers' preferences and is useful to define which features of the environment are considered to be part of the framing (Goldin and Reck 2020, p. 2764). This assumption can remain unchanged under the approach of this research proposal.

- Assumption A2) *Frame exogeneity*: $(Y_i(0), Y_i(1), Y_i^*) \perp\!\!\!\perp D_i$.

This assumption refers to the data generating process by which decision makers are assigned to frames. It is similar in nature to the assumption in the potential outcome setting that says treatment and assignment to treatment need to be independent. A2) makes sure that observed differences are due to the effect of the frames, rather than due to differences in the groups of individuals assigned to each frame. This assumption can remain unchanged as well.

- Assumption RPA) *Revealed-preference assumption*: For all $i, Y_i^* = Y_i$.

In Goldin and Reck (2020)'s setting, a framing effect is observed when assumptions A1) and A2) are satisfied and one observes $\bar{Y}(1) \neq \bar{Y}(0)$. In the context of this research proposal, a framing effect occurs if $Y_{i,k}(0) \neq Y_{i,\neg k}(1)$ for at least one k.

- Assumption A3) *Consistency Principle*: For all $i, C_i = 1 \Rightarrow Y_i = Y_i^*$.

This assumption tells us that preferences are only guaranteed to be revealed by choices for those decision makers who choose consistently across frames. This assumption also applies in the context of the data that this research proposal suggests.

- Assumption A4) *Frame monotonicity*: For all $i, Y_i(1) \geq Y_i(0)$.

Assumption A4) allows Goldin and Reck (2020) to recover aggregate information about consistency despite the fact that C_i is not observable on the individual level in their setting. The assumption requires that when a frame does affect choices, it does so in the same direction for each affected decision maker. Since C_i can be observed directly in the setting of this proposal, A4) is not necessary for the analysis of this dataset.

3 Data and Methods

Subsection 3.1 describes how the data is proposed to be collected and the kind of data that will be collected. It will also contain a short overview of browser cookies and their functionality. Section 3.2 will present how Goldin and Reck (2020) identify their parameters of interest and the simplifications that are possible when one has access to a richer dataset, as proposed here.

3.1 Data

The process of data collection is inspired by Levy (2020). In this paper, the author wrote a browser extension for Google's Chrome browser. Via a Facebook ad campaign, 8084 participants for a survey were attracted. At the end of the survey, they were offered a small reward in exchange of installing the browser extension on their device (Levy 2020, p. 9). 2262 survey participants installed the extension, and 1835 kept the extension installed for at least two weeks.

This research proposal suggests to apply the same design. Participants can be attracted via a Facebook or Google ad campaign. In a short survey, their age, gender and nationality could be elicited (for analysis of heterogeneity and the selection on observables identification approach as described in section 3.2). Afterwards, they are asked to install a small browser extension in exchange for a reward. The extension will use a short javascript code that writes a log file. This log file will keep track of whether a participant has visited a website that asks for cookie settings. It will also log whether the default setting is to accept all cookies, or whether by default only the technically necessary cookies are selected. Importantly, the extension needs not collect any information about the content of the visited websites. From a privacy point of view, this design is less invasive than the one in Levy (2020). This observation motivates the assumption that there is a sufficient amount of people who are willing to participate in such a study.

A hypertext transfer protocol (HTTP) cookie is a small piece of data that is sent from a website and stored on a users device. For the purposes of this research proposal, cookies can be classified into two groups. First, there are technically necessary cookies that ensure a website is working as intended. Such cookies could remember preceding user interactions with the site, e.g. adding an item to a shopping cart, or logging in. Second, there are cookies that are not technically necessary to ensure the website's functionality. A common example are for example third-party tracking cookies which record previously visited websites. These non-essential third-party tracking cookies can generate long-term records of a user's browsing history and can therefore manifest a potential privacy concern. Websites have an incentive to allow these cookies, as they receive third-party payments in return (common tracking cookies are e.g. Google AdSense or Facebook remarketing). The GDPR requires that all websites which target European Union or European Economic Area member states ask their users for consent before they are allowed to store non-essential cookies on a user's device. The host of a website still has a choice on how to frame this question. Either non-essential cookies are unselected by default and if the user clicks once on "accept" no tracking is possible. Or non-essential cookies are selected by default and if the user wants to avoid them it is necessary to go into the website's privacy settings and unselect tracking cookies manually.

3.2 Method

This section will describe how Goldin and Reck (2020) identify their model parameters. It will also contain a description of how the parameter identification is simplified by the dataset suggested in this research proposal.

In the first step, Goldin and Reck (2020) focus on the consistent decision makers, i.e. the subgroup of individuals whose decision does not depend on the frame. With a dataset as suggested in this proposal, it is trivial to find this group. All decision makers who are not influenced by the framing belong to the consistent decision makers (it is, of course, possible that there zero decision makers in the dataset, which would be an interesting result in itself). Once the consistent decision makers are found, using assumption A3), the consistency principle, the options they preferred can be found.

Goldin and Reck (2020)'s method is also applicable to datasets that do not contain repeated observations for each individual. It is worth noting, that Goldin and Reck (2020) mention that their method can also improve datasets that do contain repeated observations. In particular, this is the case when the *order* in which the repeated observations are generated can itself be considered a framing. For instance, this could be an issue if researchers were to analyse survey data, where the questions were not sufficiently randomized. For the dataset that is described in section 3.1 the order in which individuals see each question about cookies is assumed to follow a random process.

Goldin and Reck (2020) continue by describing the conditions for which consistent decision makers preferences can be identified when each decision maker is observed under a single frame.

- Proposition 1: $\bar{Y}_C \equiv \bar{Y}(0)/(\bar{Y}(0) + 1 - \bar{Y}(1))$
- Proposition 1.1: Under assumptions A1 - A4, $E[Y_i^*|C_i = 1] = \bar{Y}_C$.
- Proposition 1.2: Under assumptions A1 - A3, $\bar{Y}_C \geq 1/2 \Rightarrow \bar{Y}_C \leq E[Y_i^*|C_i = 1] \leq 1$, and $\bar{Y}_C \leq 1/2 \Rightarrow 0 \leq E[Y_i^*|C_i = 1] \leq \bar{Y}_C$.

Proposition 1.1 follows from the insight that, given frame monotonicity, only consistent decision-makers choose against the frame (Goldin and Reck 2020, p. 2768). Proposition 1.2 provides a partial identification result, as it defines upper and lower bounds for the fraction of frame consistent decision makers. The results under proposition 1.2 are robust to failures of frame monotonicity. In other words, it guarantees bounds in cases when there are decision makers who decide against the frame, but are still in truth inconsistent. These decision makers are defined by Goldin and Reck (2020, p. 2768) as frame defiers.

The logic of proposition 1 is illustrated in table 3.2, which is taken from Goldin and Reck (2020, p. 2769). To understand this table, it is important to know the conditions that produced the data. Here it is assumed that the researchers observe answers under both types of framing. Yet each individual's answer is only observed once under one type of framing.

TABLE 1
ILLUSTRATION OF PROPOSITION 1

	Choose Not to Enroll, Opt-In Regime, $Y_i(0) = 0$	Choose to Enroll, Opt-In Regime, $Y_i(0) = 1$
Choose not to enroll, opt-out regime, $Y_i(1) = 0$	.35	.00
Choose not to enroll, opt-out regime, $Y_i(1) = 1$	.25	.40
Fraction consistent	$E[C_i] = 0.4 + 0.35 = 0.75$	
Fraction of consistent decision makers preferring option 1	$E[Y_i^*\|C_i = 1] = \bar{Y}_C = 0.40/(0.4 + 0.35) \approx 0.53$	
Bounds on consistent preferences, without assumption A4	$0.53 \leq E[Y_i^*\|C_i = 1] \leq 1$	

NOTE.—Under frame monotonicity, top-right quadrant = 0; top-left quadrant = $1 - \bar{Y}(1)$; bottom-right quadrant = $\bar{Y}(0)$; bottom-left quadrant = $\bar{Y}(1) - \bar{Y}(0)$. $\bar{Y}_C$ is biased toward 1/2, as frame defiers are equally assigned to the top-left and bottom-right quadrants by frame exogeneity (by definition, they cannot be in the bottom-left quadrant).

To the best of my understanding, the table contains a mistake. I believe that the description for the second row of the table should read "Choose to enroll, opt-out regime, $Y_i(1) = 1$" (instead in the version in the article, the description mistakenly contains a "not": "Choose **not** to enroll, opt-out regime, $Y_i(1) = 1$").

It becomes easy to see how the fraction of consistent decision makers can be found even if each decision makers is only observed under one frame. In the example in table 3.2, 0 % of observations fall into the top-right quadrant by assumption. The top-left quadrant is the result of $1 - \bar{Y}(1)$, where $\bar{Y}(1)$ is the fraction of decision makers who chose to enroll under the opt-out framing. This number is observed by the researchers. The bottom left quadrant is the difference between the fraction of decision makers who enroll under opt-out framing and the fraction of decision makers who enroll under opt-in framing. Both fractions are observed. The bottom right quadrant is the fraction of decision makers who enroll under opt-in framing, which is, again, observed. Now the fraction of consistent decision makers who prefer option 1 can be calculated according to proposition 1. When assumption A4 is relaxed, at least a lower bound can be calculated. This way, despite the researcher not observing each decision maker under each framing, the preferences of the consistent decision makers can be recovered.

When a researcher has access to a dataset as proposed in this research proposal, the fraction of consistent decision makers preferring option 1 can be calculated directly and could be compared to the result from Goldin and Reck (2020)'s method (in table 3.2 approximately 53%). Thus, providing a way to check the method for its validity and precision in a certain setting.

For completeness, the following paragraph will shortly describe the three methods Goldin and Reck (2020, p.2769) suggest to extrapolate the preferences from the consistent decision makers to the rest of the population. As this part is not the focus of this research proposal only the main ideas are introduced here. For a detailed discussion, see Goldin and Reck (2020, p.2767).

Goldin and Reck (2020) suggest three different ways to proceed. The first approach they present explores what can be said abut they entire population without assuming additional behavioral assumptions. Without further assumptions, population preferences can only be obtained as one-directional bounds (Goldin and Reck 2020, p. 2772). The second approach is known from the sample-selection literature: adjusting for observables as individuals "select" into the group of consistent decision makers. In order for this approach to result in unbiased estimates, it is necessary to assume that all the relevant variables that link the correlation between preferences and consistency are observed by the researcher. And finally, Goldin and Reck (2020) introduce an instrumental variable based approach, which they call *decision-quality instrument*. Such an instrumental variable is a part of the decision architecture affecting only the decision makers' consistency and has no relationship with the decision maker's preferences.

4 Summary

Goldin and Reck (2020) propose a methodology to find population preferences in the presence of framing effects. This research proposal suggests to collect a unique dataset about internet users' decision on browser cookie policies. This data is collected via a browser add-on as is done in Levy (2020). The first contribution of this proposed research is methodological: with the collected dataset, one can test Goldin and Reck (2020)'s method. The second contribution of this research proposal is to find framing-consistent individual and population preferences about cookie settings; a finding that sheds light on the so-called "privacy paradox" and can be used to inform the discussion on privacy policies like the GDPR.

References

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