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Dissertation:

Economic Experiments in the Digital Age: Social Norms, Data Sharing, and Institutional Relationships

A Thesis Submitted to Obtain the Degree of:

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Presented by:

Tamas Olah

Supervisor: Prof. Dr. Christiane Schwieren

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Dissertation

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Abstract

In the evolving domain of economic behavior, the intricate dynamics of human thinking and decision-making presents a challenge to traditional theoretical frameworks. This dissertation endeavors to shed light on the ways individuals navigate the complexities of a technology-driven environment. Comprising four distinct but interconnected papers, this research explores the social norms related to personal and research data sharing, the impact of Open Science and Open Data initiatives on the scientific community, and the influence of artificial entities on human behavior.

The investigation delves into both injunctive and descriptive social norms among researchers concerning the management and dissemination of research data. It also examines the criteria under which individuals deem it appropriate to share personal data, the potential interest of various actors in accessing this data, and motivations behind why they might want it. Additionally, an experimental approach is employed to analyze the principal-agent relationship between researchers, research institutions, and funding agencies, offering insights into the current state of the scientific ecosystem. Lastly, there is the examination of social conformity in the presence of bots, questioning whether individuals align their behavior with artificial agents despite being aware of their non-human nature. This inquiry spans both objective and subjective domains, utilizing established methodologies while adapting them to novel contexts.

By maintaining a focus on scenarios that closely mimic real-life situations, this dissertation provides a contemporary perspective on economic behavior, highlighting the dynamic interplay between technology, data sharing practices, and social norms in modern society.

Acknowledgements

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Finally, this thesis is dedicated to my family: Anikó, Antal, and Edina.

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1. Introduction

The confluence of human behavior and technology represents an increasingly important area of exploration in the realm of behavioral economics, particularly as digital advancements continuously reshape societal norms and expectations. Traditional economic theories, while foundational, often lack the nuance to fully encapsulate the complex decision-making processes individuals go through in the face of rapid technological evolution. In this era of unprecedented connectivity, we are presented with a unique opportunity to examine how technological advancements influence social norms, preferences, and the overall landscape of economic behavior.

This dissertation aims to bridge the existing analytical gap by offering a detailed examination of how individuals interact with, adapt to, and are influenced by the changing digital landscape across various domains. It specifically focuses on the context of data, how data sharing is handled in the scientific community, and how ordinary people view their personal data, in addition to how individuals respond to artificial agents.

Behavioral economics, by virtue of its interdisciplinary nature, integrates insights from diverse scientific fields (Weber & Camerer, 2006), challenging the traditional economic proposition of the rational, self-interested *Homo Economicus*. Theoretical and empirical contributions from psychology, as highlighted by Thaler (2016) and Camerer (1999), suggest that real-world decision-making is often guided by heuristics and biases, influenced by the structuring of choices, incentive frameworks, and framing effects (Tversky & Kahneman, 1974). As discussed by Shiller (2003), these departures from classical models have profound implications for understanding market dynamics and individual choice behaviors, necessitating models that more accurately reflect everyday economic activities (Henrich et al., 2001).

Complementing behavioral economics, experimental methodologies offer invaluable insights into human behavior under controlled conditions, allowing for a nuanced assessment of theoretical models (Davis & Holt, 2021). According to Smith (1991), experimental economics facilitates the empirical testing of decision-making hypotheses, isolating variables to discern their specific impacts. This methodological approach, as Samuelson (2005) underscores, has evolved from a niche to a pivotal area of economic inquiry, spotlighting discrepancies between classical economic predictions and observed real-world outcomes.

The synergy between behavioral and experimental economics offers a comprehensive framework for understanding and testing theories of human decision-making and cognitive processes, thus bridging theoretical insights with empirical practices, which in turn provides a robust platform for exploring economic behaviors in real-world settings (Santos, 2011).

In the context of the unprecedented technological transformation characterizing our times, data has ascended to a position of unparalleled importance, serving as the cornerstone for the development of cutting-edge AI systems (Zha, Bhat, Lai, Yang, & Hu, 2023). Moreover, the digital economy, with its reliance on big data analytics, artificial intelligence, and machine learning algorithms, highlights the economic value of data (Novikov, 2020). Data acts as the lifeblood of the digital marketplace, enabling businesses to refine their strategies, enhance customer experiences, and innovate products and services. In this context, it is imperative to cultivate a culture of data utilization and transparent practices thereof to sustain growth and competitiveness.

The need for high-quality, accessible data transcends the need of private enterprises; it is also important for academia, being a key component in the Open Science movement's vision. This promotes the sharing of research data not only to bolster scientific reproducibility (a foundational pillar of the scientific method) but also to facilitate the reusability of data (Hasnain & Rebholz-Schuhmann, 2018), thereby catalyzing the advancement of knowledge and bringing various benefits to a wide array of disciplines (Arzberger et al., 2004; Huston, Edge, & Bernier, 2019). The Open Science paradigm is poised to revolutionize the scientific landscape by democratizing access to data and ensuring that the fruits of scientific labor are available to a wider community, fostering innovation and accelerating the pace of discovery.

This dissertation aims to elicit public perceptions surrounding this evolving technological and scientific landscape, exploring optimal approaches for conducting research in this new era. Through a combination of laboratory experiments and extensive international survey-experiments conducted with my co-authors, we seek to offer insights into societal attitudes towards open science, data sharing, and the principal-agent dynamics that exist in scientific research.

In this line of investigation, the measurement of social norms pertaining to data sharing emerges as a critical area of inquiry. Understanding the collective attitudes and behaviors that define how individuals and institutions perceive and engage with data sharing practices is vital for identifying barriers to open science and the free flow of information. This endeavor not only illuminates the ethical and social considerations underpinning data sharing but also provides insights into how these norms can be nurtured and promoted within the scientific community and beyond.

An intriguing dimension of our digital age is the interaction between humans and artificial agents, particularly as can be seen in online environments. The phenomenon of social conformity (a tendency to align one's behavior with that of a surrounding group) extends into the realm of digital interactions, raising questions about how individuals respond to the presence of bots. The extent to which people conform to social norms in the presence of artificial agents has implications for understanding the dynamics of human-computer interaction and the influence of automated systems on decision-making processes. This aspect of our research sheds light on the nuanced ways in which technology mediates social behavior and the potential for artificial agents to shape social norms and expectations in online settings.

As we delve deeper into these themes, the central role of data in science and the digital economy, alongside the imperative to measure and understand social norms regarding data sharing, becomes ever more apparent. Through this exploration, we aim to contribute to the broader discourse on the ethical, social, and economic dimensions of data in our increasingly digital world.

1.1 Motivation and Objectives

The landscape of science and technology is evolving at an unprecedented pace, necessitating a reevaluation of their impacts on human behavior and societal structures. This dissertation leverages the tool sets of behavioral and experimental economics to construct a comprehensive framework for understanding these dynamics. The primary objectives are structured around key areas of inquiry:

Unveiling Social Norms and Institutional Dynamics in the Evolving Scientific Ecosystem: The scientific arena is undergoing a significant transformation, propelled by technological advancements and policy shifts. This evolution introduces a complex interplay of divergent incentives and preferences among various stakeholders, necessitating a thorough exploration to foster alignment between them.

Investigating Perceptions and Attitudes Towards Information Utilization: In an era where data-driven strategies yield substantial benefits across sectors, understanding public sentiment towards the use of personal information becomes critical. This inquiry aims to illuminate the perspectives of individuals whose data are harnessed, thereby informing policymakers and maximizing societal gains.

Examining Human-Artificial Agent Interactions: The technological leap has rendered interactions with artificial agents nearly indistinguishable from human engagements in certain contexts. This development poses intriguing questions regarding societal attitudes towards and interactions with these entities.

Ultimately, this research endeavors to expand the boundaries of economic knowledge by harnessing technological advancements, methodological innovations, and the power of interdisciplinary collaboration.

1.2 Main Contributions to the Literature

This dissertation consists of four papers, each aimed at advancing the field of economics through the application of behavioral and experimental methods. This work is driven by a commitment to extend our understanding to modern phenomena and build upon existing economic research. Each paper contributes original ideas and research findings, adding new insights to the field. The collaborative efforts of co-authors played a crucial role in achieving the research goals, enriching the dissertation with diverse perspectives and expertise.

The chapter **Social Norms regarding Data Sharing in publicly funded research** explores how researchers from different countries (United States, United Kingdom, Germany) and fields (Life Science, Social Science) view Open Science with a focus on Open Data. It examines both injunctive and descriptive norms regarding a variety of situations scientists encounter, as well as their thoughts and (claimed) practices. The results indicate a marked difference between attitudes in European countries and the United States. Open Science and data sharing appear to be more established and institutionalized in the US, while in Europe researchers are mainly motivated by individual factors when sharing their data. An important principal-agent relationship between Researchers, Research Institutions, and Funding Agencies is also highlighted. On the other hand, differences between the fields are insignificant in most cases. We also find little to no evidence of a gap between the attitudes and behaviors of researchers.

Social norms and motivations regarding data examines data from the other side compared to the first chapter. This paper takes a look at how data subjects from various countries perceive the use of their data. This survey-experiment investigates data from a number of domains to see with whom participants think it is appropriate to share with, as well as what might motivate various actors to want to access it. We find that participants not only care about the information content of data but about the purpose of its generation as well. They also have different levels of willingness to share data with different actors, considering sharing for research purposes relatively appropriate, while sharing with governments or businesses very inappropriate. We uncover that this is likely due to participants thinking researchers are being motivated by altruism, while the other two are primarily ascribed self-serving motives.

The paper **Data Sharing in Science: The Principal-Agent relationship between Researchers, Research Institutions and Funding Agencies** like the previous also builds on insights uncovered in the first chapter. The aim was to see how these actors work together (or against each other) in science to generate publications and data. Here we utilize a laboratory experiment to examine the intricate principal-agent relationship between the three actors. Funding Agencies are principals to both Researchers and Research Institutions, while there is also a principal-agent relationship between the second two. This dual relationship from the perspective of Researchers is further complicated by their incentives being more closely aligned to those of the Research Institutions. The results indicate a willingness on Researchers' part to share their data for little to no individual benefit if it is formally required of them, even if this requirement is not enforced. It is important to note that this only goes above the minimum level if they have resources to spare for this purpose.

The last paper **Social Conformity to bots** explores if social conformity exists even if participants are clearly told that they are interacting with bots. This approach also avoids any deception, making it possible to pursue the research of social conformity while following the requirements of experimental economics. Implemented as a laboratory experiment it examined conformity in both the objective and subjective domains to a majority of three bots. Different treatments also investigated how conformity develops depending on if bots oppose the participant's subjective opinions, or support a more extreme version of it.

The results show conformity in both the objective and subjective domains, regardless of the majority stance. There is also evidence that female participants are more influenced by bots, as well as the different types of conformity being motivated by different factors.

In summary, the chapters in this dissertation provide insights from experimental and behavioral domains. Table 1.1 briefly summarizes each paper and the approaches used.

Paper 1 - Social Norms regarding Data Sharing in publicly funded research (chapter 2): *Experimental Approach:* Online survey experiment with researchers. *Behavioral Approach:* Analysis of injunctive and descriptive social norms between researchers in different fields and countries. *Co-author:* Christiane Schwieren *Status:* Submitted for publication in May 2024
Paper 2 - Social norms and motivations regarding data (chapter 3): *Experimental Approach:* Online survey experiment experiments. *Behavioral Approach:* Analysis of social norms regarding with whom participants would be willing to share personal data, and their perceived motivations. *Co-author:* Leon Houf *Status:* Will be submitted for publication
Paper 3 - Data Sharing in Science: The Principal - Agent relationship between Researchers - Research Institutions - Funding Agencies (chapter 4): *Experimental Approach:* Lab experiment, between-subject design with six treatments. *Behavioral Approach:* Examination of the principal-agent relationship in academia under different incentive structures. *Co-author:* Christiane Schwieren *Status:* Will be submitted for publication
Paper 4 - Social Conformity to bots (chapter 5): *Experimental Approach:* Lab experiment, within-subject design regarding social conformity, between-subject design concerning the opinion of the majority *Behavioral Approach:* Analysis of social conformity to a supporting or opposing majority, and what traits are behind this process *Status:* Will be submitted for publication

Table 1.1: Summary of Papers and Approaches

The employed techniques range from lab experiments (both individual and group-based) to large survey-experiments conducted online. From the behavioral perspective, methods range from classical decision-making, trust, and risk measures, as well as the effects of the Big Five personality traits. In addition to the above, this work is focused on the social aspect present in each situation, which encompasses topics such as social norms and conformity, a wide range of potential motivations, as well as possible collusion between certain actors.

1.3 Structure of this Document

The thesis is structured to follow the four papers discussed one after the other, each with its abstract, introduction, methods, experiment design, limitations, and conclusion. Each paper articulates its aims separately, as well as the employed methods, and derived results. The literature used across the papers can be found consolidated at the end of the document. Finally, Chapter 6 encapsulates the work's primary takeaways, contributions, and conclusions.

2. Social Norms regarding Data Sharing in publicly funded research

Authors

Tamas Olah & Christiane Schwieren

Abstract

This study investigates descriptive and injunctive social norms regarding data sharing and Open Science in publicly funded research, employing a modified version of the method by Krupka and Weber (2013), further refined by Schmidt, Heinicke, and König-Kersting (2022). We recruited 281 participants, including PhD students and researchers at more advanced career stages, from the United States, the United Kingdom, and Germany across the life and social sciences.

Our findings reveal pronounced differences across countries but minimal disparities between disciplines. Moreover, the discrepancy between researchers' attitudes and actual data sharing behaviors was generally small, manifesting only under certain conditions. Participants also reported on their personal data sharing practices. Here, significant variations were observed among researchers based on their country of origin, discipline, and career stage. A vast majority indicated that they share their data, recognizing it as a hallmark of good scientific practice. However, there was also a consensus that mandatory data sharing policies could hinder their work. The study reveals stark contrasts between researchers in the United States and their European counterparts, both in terms of social norms and self-reported practices related to data sharing. These findings suggest that data sharing in the U.S. is characterized by a more formalized and institutional framework, whereas in Europe, it is predominantly motivated by individual researchers' initiatives.

Keywords

Social Norms, Open Science, Data Sharing, Academia

2.1 Introduction

In recent years, the sharing of scientific data has emerged as a crucial component of the Open Science movement and is comprised of concepts such as Open Access, Open Data, and Open Software among many others. With the growing importance of data-driven research and the increasing complexity of scientific challenges, there is a need for more open and collaborative approaches to research that allow for the sharing of data, methods, and results. Sharing data can lead to increased transparency, reproducibility, and accountability in research, while also promoting greater collaboration among researchers, potentially even making one's own work more efficient (Alter & Gonzalez, 2018; European

Commission, 2019; Fecher, Friesike, & Hebing, 2015; Figueiredo, 2017; Martone, Garcia-Castro, & VandenBos, 2018; Munafò et al., 2017; UNESCO, 2021).

Despite these benefits, the sharing and accessing of data also raises numerous questions (Wendelborn, Anger, & Schickhardt, 2023). The lack of standardization in data sharing policies and practices between funding agencies (especially between different countries and disciplines) is a serious hurdle to achieving the goals and reaping the benefits of Open Science. While many funding agencies have made writing a data management plan a requirement for grant applications, only a few outright stated data sharing itself as a requirement. Moreover, there is considerable variation in the specifics of what is required and how it is enforced. Some funding agencies have started to take past data sharing efforts into consideration during their evaluation process (European Commission and Directorate-General for Research and Innovation and Cabello Valdes, C and Rentier, B and Kaunismaa, E and Metcalfe, J and Esposito, F and McAllister, D and Maas, K and Vandevelde, K and O'Carroll, C, 2017), while others focus more on the enforcement of their already existing policies (NIH, 2023). Some agencies require data sharing only after a certain period of time has elapsed since the publication or completion of the project, while yet others require immediate sharing upon the collection of data or the publication of research findings. Furthermore, the mechanisms for sharing data can vary widely between disciplines and even between different specializations, ranging from data repositories to personal websites. In some contexts, even email exchanges are implied as acceptable by not setting any concrete requirements (Tenopir et al., 2011). Funders also consider enacting various policies, that also change over time, thus creating a rapidly developing environment (Anger, Wendelborn, Winkler, & Schickhardt, 2022).

This can lead to situations where researchers are on one hand unsure about what is expected of them in terms of data sharing, and on the other hand face obstacles in trying to access or reuse data from others. Additionally, researchers themselves have reservations about sharing data, based on concerns over confidentiality, recognition, and the fear of the data being scooped by competitors or free riders (Alter & Gonzalez, 2018; Kowalczyk & Shankar, 2011; Longo & Drazen, 2016; Martone et al., 2018). These reservations are influenced by cultural and institutional factors of the researchers' work settings, leading to differences in data sharing behavior between different disciplines (Nelson, 2009; Tedersoo et al., 2021) and countries (Tenopir et al., 2015).

Our survey-experiment has several aims: firstly, to shed light on researchers' perceptions on data sharing. Secondly, it aims to understand differences in perceptions between researchers in the United States, the United Kingdom, and Germany in different disciplines: Life and Social Sciences, regarding data sharing. To achieve that, the study focuses on two types of norms: descriptive norms, which are beliefs about what researchers in a specific setting are actually doing, and injunctive norms, which are beliefs about what researchers in this context think should be done.

The survey was designed to gather this information from a range of subtopics related to data sharing, including the following factors:

- Perceived completeness of data that should be shared
- Concerns about data sharing
- Potential incentives to share data
- Who should apply sanctions in case of non-compliance to data sharing policies
- Who should catalyze data sharing

In addition to collecting data on participants' normative attitudes and beliefs regarding data sharing, the survey also includes questions regarding their demographic information and personal opinions on the subject.

By collecting data on the attitudes and beliefs of researchers across different countries and disciplines, this study can provide a detailed understanding of the different factors that affect data sharing practices. Consequently, it seeks to identify effective strategies to foster increased data sharing within the scientific community, across or within specific disciplinary and national settings.

2.2 Survey Design

2.2.1 Hypotheses

We anticipate differences in attitudes towards research data sharing among researchers from different countries and disciplines based on several reasons. In the Life Sciences, generating research data requires significantly more time and resources than in the Social Sciences. Whether this might drive more positive or more negative attitudes toward data sharing remains to be found. National research cultures are shaped by their institutional background leading to unique incentives or pressures, which results in different levels of commitment to data sharing among researchers. This includes differences in reasons for concerns regarding data sharing, including worries about subject privacy, and the risk of data misuse and misinterpretation. Moreover, the types of incentives offered and the repercussions of non-compliance vary both across different regions and scientific disciplines.

In addition to differences between disciplines and national cultures, we expect a discrepancy between stated attitudes and actual behaviors with respect to data sharing. Although researchers may express supportive views on data sharing (injunctive norms), these beliefs do not always manifest in their practices (descriptive norms). This attitude-behavior gap has been widely documented for many different topics (Kaiser, Byrka, & Hartig, 2010; Papaoikonomou, Ryan, & Ginieis, 2011; Young, Hwang, McDonald, & Oates, 2009). It underscores the importance of identifying and understanding the barriers that prevent the alignment of researchers' attitudes with their actions.

Thus we hypothesize a set of differences to exist between researchers working in different environments:

1. Differences between countries
2. Differences between disciplines
3. Differences between types of norms (descriptive vs injunctive)

2.2.2 Respondents

We used a between-subject design considering countries, disciplines, and injunctive vs descriptive norms. A call for participants to sign up for the survey was posted on different social media platforms, recruiting PhD students and researchers in other career stages from the designated categories. We incentivized them with a reward of around 5€, depending on their performance, in the form of an Amazon Gift Card for about 15 minutes of filling out the survey. They were first asked to indicate the country and discipline they work in, to allow us to sample a similar number of participants for each discipline/country combination. To ensure anonymity, this sign-up was handled separately from the main survey. Overall 281 participants (35.23% PhD students, 43.42% Postdoctoral researchers, 21.35% Senior researchers) completed the survey with an average age of 35.49 years (SD = 7.037), 41.64% of whom were female.

Based on the information provided in the sign-up, a random set of participants were assigned to each of the corresponding treatments and sent a link in an email pointing to the main survey which they were asked to complete at their leisure. Due to the nature of our recruitment process, we have somewhat different numbers of observations in the different treatments. As seen in Table 2.1, we have 12 treatments with approximately 20 participants in each.

Country	discipline	Norm	Observations
US	Social Science	Injunctive	24
US	Social Science	Descriptive	22
US	Life Science	Injunctive	21
US	Life Science	Descriptive	25
UK	Social Science	Injunctive	22
UK	Social Science	Descriptive	24
UK	Life Science	Injunctive	22
UK	Life Science	Descriptive	14
GER	Social Science	Injunctive	22
GER	Social Science	Descriptive	27
GER	Life Science	Injunctive	34
GER	Life Science	Descriptive	24

Table 2.1: Treatments and number of observations

2.2.3 Procedure

The survey was implemented using the oTree (D. L. Chen, Schonger, & Wickens, 2016) platform and utilized the method from Krupka and Weber (2013) with the refinement from Schmidt et al. (2022) for the elicitation of social norms. First, however, participants were presented with several allocation decisions between themselves and a random other participant to measure their Social Value Orientation (McClintock & Allison, 1989), which we assess to control for social preferences that might affect data sharing.

To get participants accustomed to the experimental methodology, an example of the social norm scenarios was initially presented. This was followed by the situations of interest, related to data sharing. Participants were asked to distribute 100 points across a range of options, based on the perceived appropriateness or frequency of each option within their specific discipline and country. Importantly, participants were instructed to base their responses on perceived norms within their discipline and country, rather than personal opinions, choosing the option they believed was most aligned with the injunctive norms in one condition, and the most common behavior (descriptive norms) in another. As in the method outlined by Schmidt et al. (2022) participants received a bonus for each point they allocated to the alternative which received most points from others in their condition.

The experiment encompassed five distinct scenarios designed to probe attitudes and behaviors toward various facets of data sharing. These scenarios were presented sequentially and in the same order to all participants. Participants were not informed of the responses of their peers during the experiment. Each participant was assigned to evaluate either injunctive or descriptive norms exclusively.

Upon completion of these scenarios, participants received additional questions about their personal attitudes and practices regarding data sharing, next to basic demographic details. We asked about participants' direct engagement with data sharing, such as their practices of sharing and using others' data, perceptions of data sharing as a potential hindrance to their work, and its recognition as good scientific practice. Furthermore, questions sought participants' perspectives on the optimal timing and settings for data sharing. In this section, direct questions were employed to reduce the complexity and duration of the survey but still allow for a comparison between individual opinions and perceived norms.

2.3 Situations

2.3.1 Completeness of data to be shared

The first situation that we presented to our participants concerned the type of data that should be shared (in terms of elaboration and completeness) and was described as follows: ”Researcher A works on a publicly funded research project financed by Funding Agency B, and decides to share their data in a data repository.”
The participants were given the following alternatives (brackets indicate how these were encoded, not shown to participants):

- ”Researcher A only provides the raw files that are stored on their computer just the way they were. This takes just a few moments of their time. (raw)
- Researcher A shares their data with basic instructions and documentation, but does not provide details. This takes a moderate amount of time but makes it difficult for others to use it. (basic)
- Researcher A makes their data as open as possible, and includes all information so others would be able to use it. All this takes a considerable amount of their time. (full)
- Researcher A shares their data, but deliberately makes it difficult for others to understand and use. (sabotaged)”

Participants were asked to distribute 100 points between these options, indicating how appropriate (or frequent) other researchers in their discipline and country would think they are.

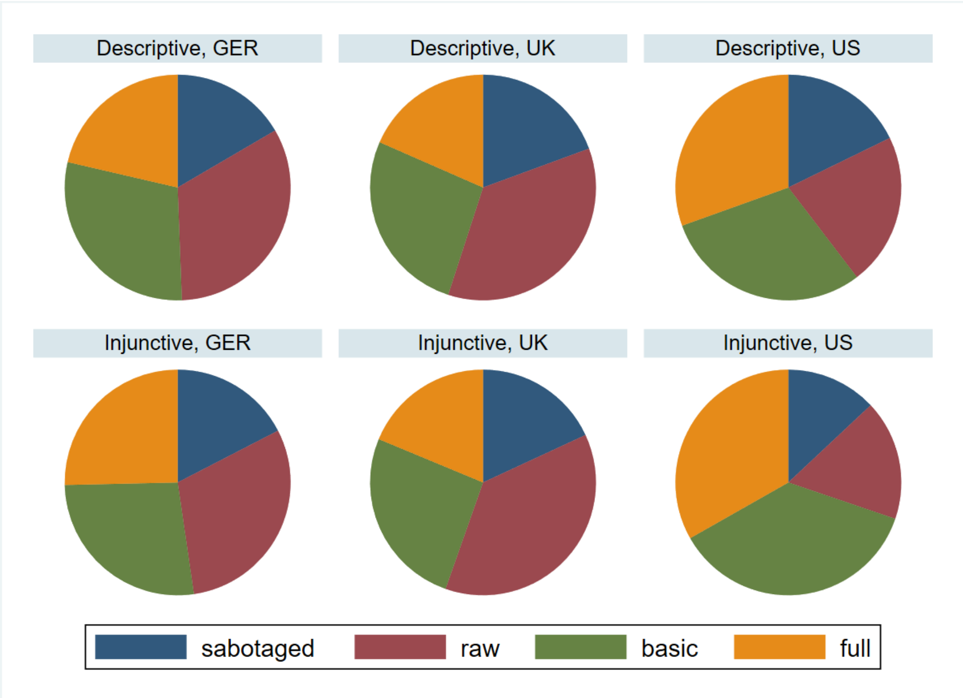

Figure 2.1: Type of data that should be shared by Countries

Figure 2.1 shows how many points respondents from the different countries assigned to each answer alternative. We found large differences between the examined countries. When comparing Europe to the United States, it appears more appropriate to share raw data compared to basic data ($p<0.001$ in the UK and $p=0.011$ in Germany). Compared to raw data, sharing basic ($p<0.001$) and full data ($p=0.001$) is far more appropriate (and frequent) in the US. This indicates that the practice of data sharing might be more developed in the United States, favoring more complete and better-documented data compared to Europe. Surprisingly, sabotaging data is not completely inappropriate in either of the countries ($p<0.001$ compared to 0 in all countries), although in the US it is considered significantly less appropriate than in the UK ($p=0.029$). The tightness of norms, measured by the variance in the distribution of points, also differs between countries. Social norms are generally most focused in the United Kingdom while being looser in Germany and the loosest in the United States. We do not find significant differences between the norms for Social and Life Sciences regarding the completeness of the data to be shared.

The attitude-behavior gap is hardly discernible in our survey. Only US Life Sciences exhibit a difference between their attitudes and behaviors (Figure 2.2).

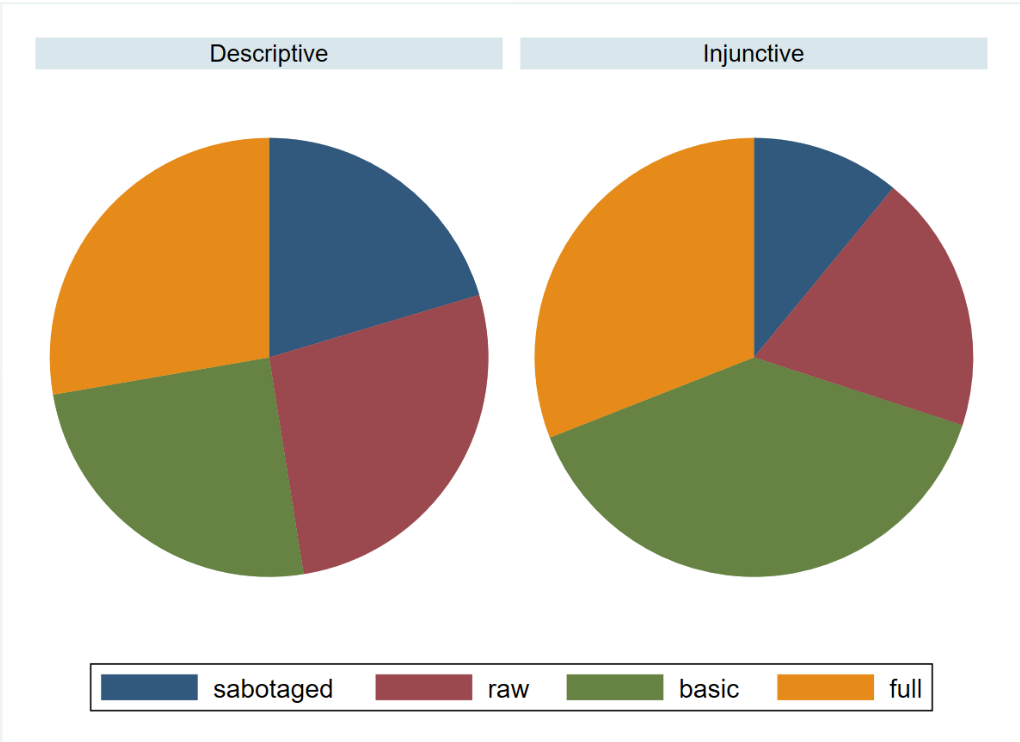

Figure 2.2: Type of data in US Life Science

The difference between injunctive and descriptive norms in the United States is in line with our expectations. Sabotaging data is perceived to be more frequent (descriptive norm) than appropriate (injunctive norm) ($p=0.03$). Sharing basic data is more appropriate while being less frequent ($p=0.008$). Contrary to our expectations, we do not find the same pattern in the other countries and disciplines.

2.3.2 Concerns

The second situation participants were presented with was:
"Researcher A works on a publicly funded research project financed by Funding Agency B. In the funding conditions B requires A to share their data. A refuses to do this after the project is finished. The reason Researcher A gives for not sharing the data is that it...

- takes too much time (time)
- creates a risk for the privacy of their subjects (privacy)
- creates the risk that others would misunderstand or misuse it (misuse)
- is not in their own scientific interest (interest)"

and just as before, participants were asked to distribute 100 points between the options indicating how appropriate (or frequent) other researchers in their discipline and country think they were.

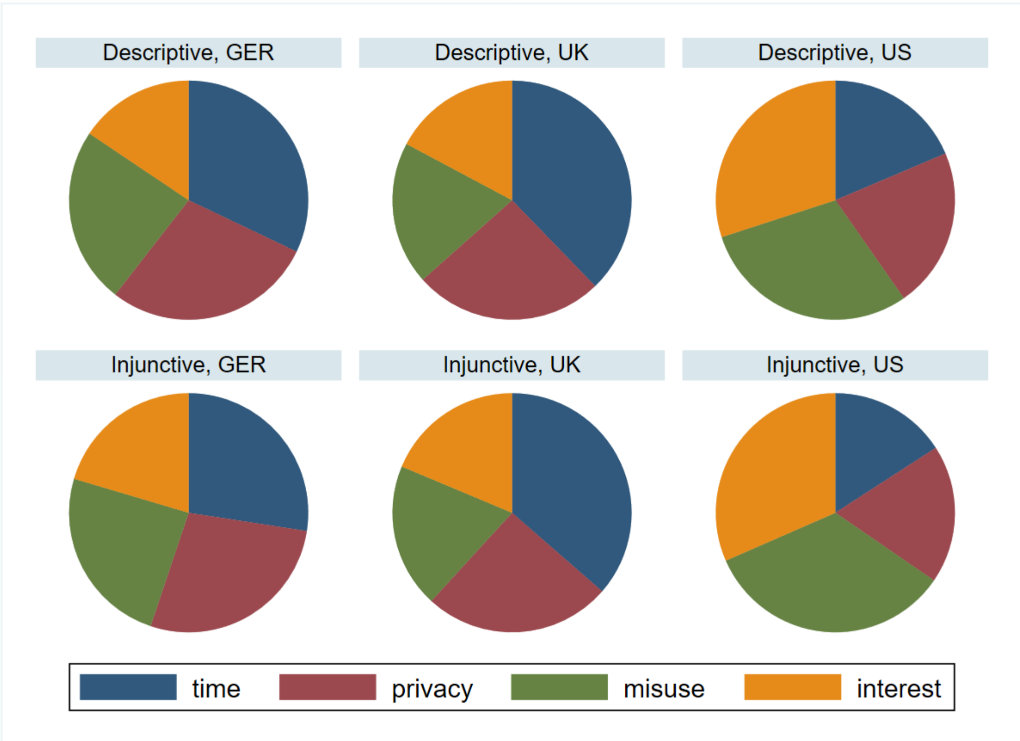

Figure 2.3: Concerns by Countries

As can be seen in Figure 2.3, in this situation we again found large differences between the European countries and the United States. Researchers in the UK are more focused on time compared to the other two countries ($p<0.001$), while in Germany researchers' focus is stronger both on time ($p<0.001$) and the risk to their subjects' privacy ($p=0.003$) compared to the US. As a stark contrast to this, US researchers are more worried about the potential misuse or misunderstanding of their data ($p<0.0001$) compared to researchers in the UK and ($p<0.001$) Germany, and the risks it may pose to their scientific interest ($p<0.0001$) compared to both European countries.

Surprisingly, there are again no significant differences between the norms in the Social and Life Sciences. Just as before, we observe a difference in the tightness of norms by considering the variances. Norms again are the tightest in the United Kingdom, looser in Germany, and the loosest in the United States.

2.3.3 Incentives

"Researcher A works on a publicly funded research project financed by Funding Agency B. A decides to share their data openly with all relevant documentation and metadata, because..."

- the community expects this, considering it good scientific practice (gsp)
- Researcher A personally considers it important (personal)
- Funding Agency B would punish them by not allowing to hand in a grant application in the next funding round if they did not share their data (punish)
- Funding Agency B grants extra money for sharing data (money)"

Just as before, participants were asked to distribute 100 points between the options indicating how appropriate (or frequent) other researchers in their discipline and country think they are.

As with the previous situations, Figure 2.4 shows that significant differences were found between the European countries and the United States. European researchers indicate that they are primarily motivated by considering data sharing to be part of good scientific practice and to a lesser extent by personally considering it important ($p=0.005$ when comparing Germany to the US and $p<0.001$ when comparing the UK to the US). Researchers in Europe give little thought to the possibility of punishment, whereas in the United States, the main incentive for sharing appears to be the fear of punishment ($p<0.001$ compared to either Germany or the UK). This hints at data sharing being far more institutionalized and regulated in the US as compared to Europe, where the practice appears to be more informal and based on individual or community initiatives. Interestingly, researchers seem to be able to judge the lack of enforcement and punishment in Europe relatively well (Anger et al., 2022), while they are potentially overestimating these in the US. Although the NIH promises monitoring and potential sanctions in case of non-compliance, it remains rather vague about the subject (NIH, 2023). It is also important to note that punishment is not only perceived as a common motivation for sharing data in the US but it is also seen as the most appropriate one. This suggests that researchers in the United States are in agreement with the current status quo and are willing to put up with potential punishments in case of non-compliance.

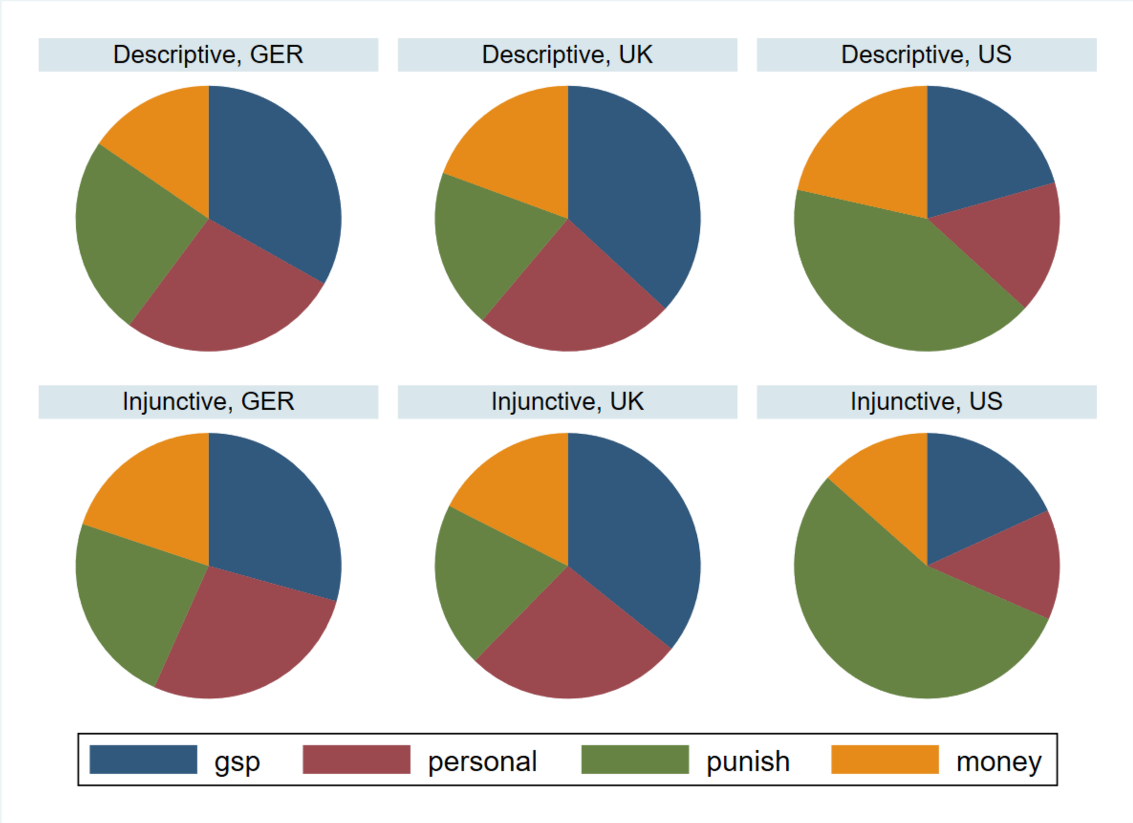

Figure 2.4: Incentives by Countries

Just as in the previous situations, the norms are much tighter in Europe compared to the US considering the variance in the surveyed norms. As before, the UK appears to be the most focused, followed by Germany, with the US being the least focused. There is also little to no difference between scientific disciplines and between the attitudes and behaviors of researchers.

2.3.4 Sanctions

"Researcher A works on a publicly funded research project financed by Funding Agency B at Research Institution C. In the conditions for funding the project, B has stipulated that A must openly share their research data in a repository. Despite agreeing to these conditions A has failed to implement data sharing."

They were then given the following alternatives:

- Funding Agency B sanctions Researcher A (FA)
- Research Institution C sanctions Researcher A (RI)
- The scientific community sanctions Researcher A (community)
- Researcher A faces no sanctions (none)

Just as before, participants were asked to distribute 100 points between the options.

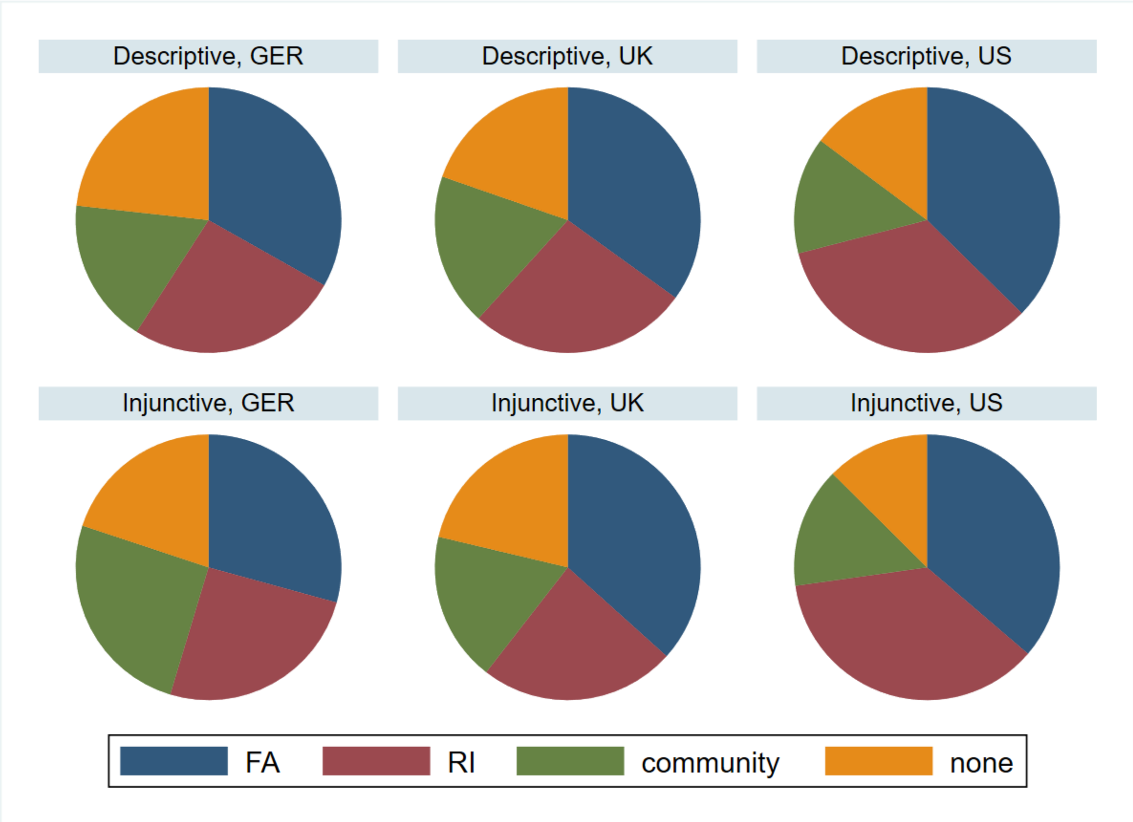

Figure 2.5: Sanctions by Countries

As seen in Figure 2.5, sanctioning by the funding agency is perceived to be both the most frequent compared to research institutions ($p=0.003$ in Germany, $p<0.001$ in the UK), and also the most appropriate compared to research institutions ($p<0.001$ in the UK) in all of the surveyed countries. Compared to the other two countries, American researchers indicated that sanctioning by a research institution is more frequent ($p=0.008$ compared to the UK and $p=0.006$ compared to Germany) and appropriate ($p<0.001$ compared to the UK, $p<0.001$ compared to Germany) in their country. Sanctioning by the community is seen as relatively more appropriate in Germany compared to the United Kingdom ($p=0.012$) and the United States ($p=0.001$). Facing no sanctions is perceived to be more frequent ($p=0.037$) and even appropriate ($p=0.023$) in Germany than in the United States. Curiously, even though clearly stating noncompliance with the funding conditions in the vignette, we not only find that facing no sanctions is said to occur, but that the appropriateness of such an outcome is not zero ($p<0.001$ in all cases).

Similarly to the previous vignettes, we find that norms in the UK are the tightest. In the cases of sanctioning by the funding agency and sanctioning by the community, the norms are the loosest in the United States. Meanwhile, the norms regarding sanctioning by the research institution and facing no sanctions are the loosest in Germany.

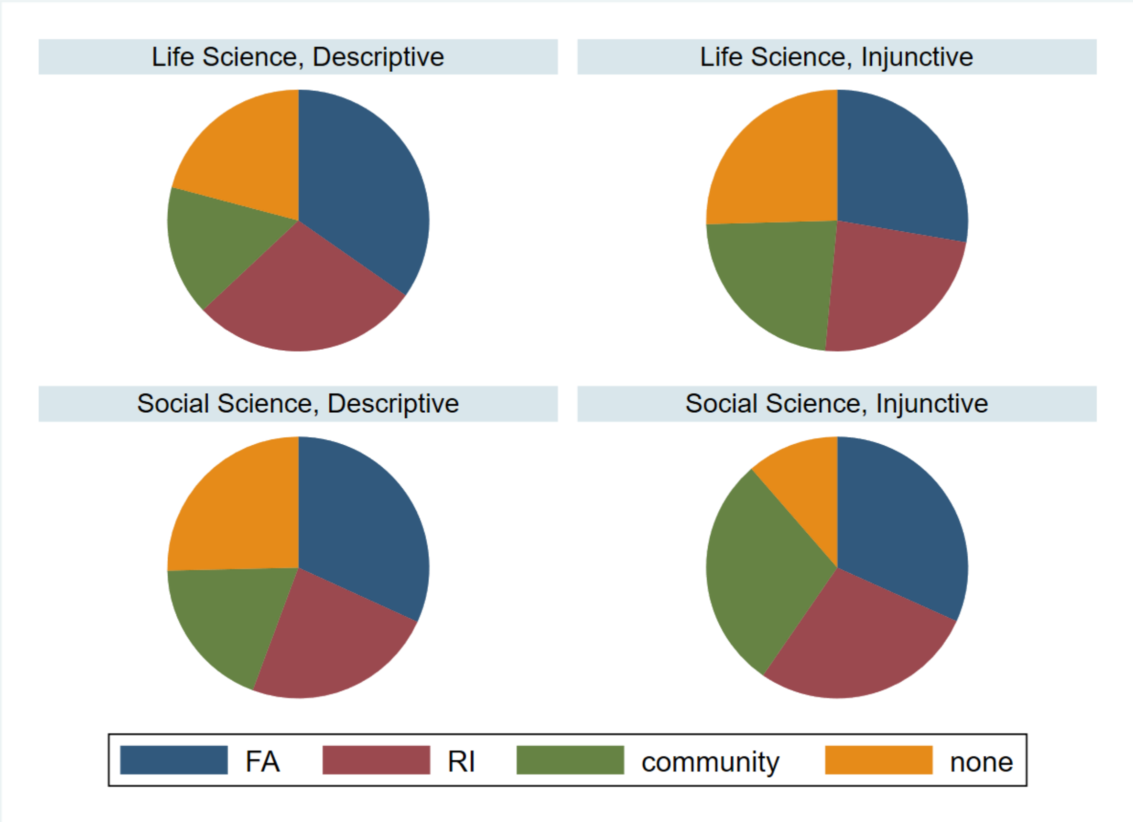

Figure 2.6: Sanctions in Germany

We find a small difference between the descriptive and injunctive norms in Germany as seen in Figure 2.6 in both the life and social sciences. In the life sciences, sanctioning by the funding agency is considered more frequent but less appropriate (p=0.026), while sanctioning by the community is considered to be somewhat more appropriate although less frequent (p=0.09).

Meanwhile, in the social sciences, there is weak evidence that sanctions enforced by the scientific community are considered appropriate but less frequent (p=0.057), and facing no sanctions at all is seen as more frequent while being far less appropriate (p=0.013).

2.3.5 Catalyst

The last situation participants were presented with stated:
”Researcher A works on a publicly funded research project financed by Funding Agency B, at Research Institution C. In this situation, the catalyst (main motivator) for data sharing is/should be...

- Researcher A (R)
- Funding Agency B (FA)
- Research Institution C (RI)
- the journal Researcher A plans to publish in (journal)
- other researchers (Rs)”

Just as before, participants were asked to distribute 100 points between the above options indicating how appropriate (or frequent) other researchers in their discipline and country think they are.

Figure 2.7 illustrates that there are again large differences between the European countries and the United States regarding the ideal catalyst of the data sharing process. Similarly to previous situations, Germany and the United Kingdom exhibit very similar tendencies. Data sharing appears to be more individually motivated in these countries, emphasizing the role of the individual researchers in the data sharing process (p<0.001 compared to the US regarding both types of norms). Meanwhile, respondents from the United States indicated that the role of research institutions is crucial to the process, as it is considered very frequent (p=0.004 compared to the UK, p=0.001 compared to Germany) and appropriate (p<0.001 compared to the UK, p<0.001 compared to Germany).

An additional interesting finding is that although in Europe the individual researcher is seen as the main catalyst in the process, in all cases the research community itself is not seen as a frequent or appropriate motivator for data sharing. Aside from this, the journals are also ranked low on this scale. This indicates that despite them usually having policies about data sharing, this is not seen as an important motivation by our participants.

Just as previously, in most cases, we find that norms are the tightest in the UK while being looser in Germany, and the loosest in the US. Considering journals to be the catalyst is the exception to this rule, as the difference in variance is not significant across the three countries.

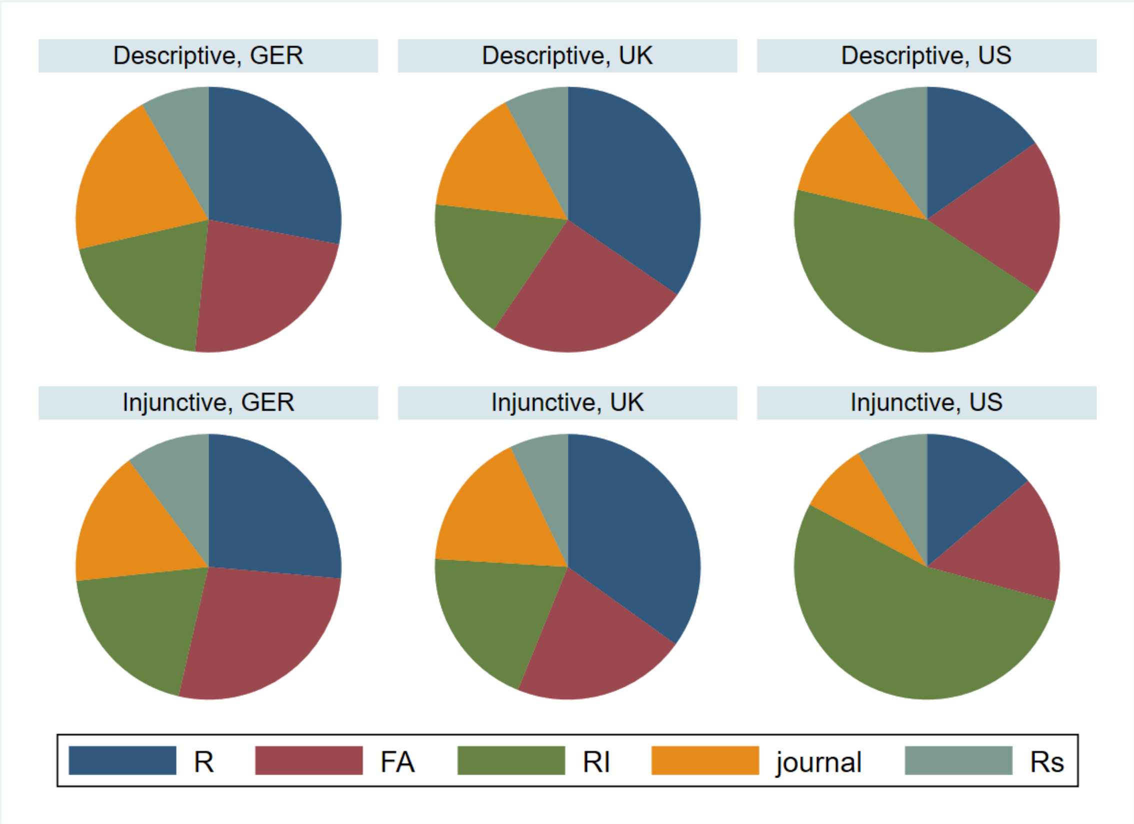

Figure 2.7: Catalyst by Countries

2.4 Individual Opinions

The findings of our survey indicate that there is a rather high willingness among researchers to share their research data. The percentage of participants (87%) who claimed to share their research data is considerably higher than what previous studies have shown (Alsheikh-Ali, Qureshi, Al-Mallah, & Ioannidis, 2011; Federer et al., 2018; Savage & Vickers, 2009; Tenopir et al., 2011).

Moreover, a majority of our participants (85%) consider data sharing to be part of good scientific practice (GSP), which illustrates the changing attitudes towards data sharing among researchers.

However, it is interesting to note that only 63% of the participants reported using data shared by others, indicating potential barriers to reusing data. Another noteworthy finding from our survey is that, despite the high rates of data sharing and considering it good scientific practice, a substantial portion of respondents (64%) reported that mandatory data sharing requirements impede their work. This suggests that there may be wide-reaching concerns and hurdles around data sharing, pointing to the importance of the surveyed norms promoting further data sharing.

Furthermore, our survey results also revealed significant differences in attitudes and practices regarding data sharing among researchers from different countries, disciplines, and positions. These differences suggest that cultural, disciplinary, and institutional factors play a major role in shaping attitudes toward data sharing.

When breaking down responses to our survey questions by countries (Table 2.2), a similar pattern can be found as in the vignettes, where European researchers are very much alike, while Americans differ significantly from researchers in the other two countries.

Country	Share data	Use data	Impedes work	GSP
GER	82%	61%	72%	88%
UK	80%	57%	72%	71%
US	99%	72%	47%	96%

Table 2.2: Attitudes towards data sharing by countries

A significantly higher percentage of researchers in the United States claim to share their data compared to their German ($p<0.001$) and British ($p<0.001$) counterparts, and they also use data shared by others more frequently compared to German researchers ($p=0.5$). Furthermore, a much larger proportion of American researchers consider data sharing to be a part of good scientific practice ($p=0.05$ compared to UK and $p<0.001$ compared to Germany), while a much smaller part of US researchers believe that mandatory data sharing impedes their work in contrast to researchers in Germany ($p<0.001$) and the United Kingdom ($p<0.001$). It is particularly interesting to note that the proportion of American researchers claiming to share their data is not statistically different from being at 100%, indicating an especially strong culture of data sharing in the United States.

discipline	Share data	Use data	Impedes work	GSP
Life Science	98%	59%	57%	96%
Social Science	100%	85%	37%	96%

Table 2.3: Differences in attitudes between disciplines in the US

As seen in Table 2.3, we found significant differences in the attitudes and practices of researchers in the United States depending on their discipline. While both disciplines share their data equally frequently and consider it good scientific practice to do so, participants from the social sciences use the data of others far more ($p<0.001$) and consider it less of a hurdle to share ($p=0.06$).

discipline	Share data	Use data	Impedes work	GSP
Life Science	84%	62%	70%	83%
Social Science	91%	65%	57%	88%

Table 2.4: Attitudes towards data sharing by disciplines

Table 2.4 shows that despite numerous key differences between countries, the same cannot be said about the two disciplines we focused on. The only significant difference between disciplines when considering all countries is whether or not researchers consider mandatory data sharing to impede their work. This opinion is considerably higher ($p=0.029$) in Life sciences compared to Social sciences.

Table 2.5 shows sizable differences between researchers in different career stages. PhD

Position	Share data	Use data	Impedes work	GSP
PhD	84%	73%	64%	80%
Postdoc	90%	61%	66%	91%
Senior	87%	53%	60%	83%

Table 2.5: Attitudes towards data sharing by positions

students use data shared by others significantly more than researchers in higher ranks (p=0.06 compared to Postdocs and p=0.013 compared to senior researchers). Curiously, Postdocs consider data sharing to be good scientific practice significantly more than PhD students (p=0.017). However, this does not lead to significant differences in sharing data or considering mandatory sharing to impede their work.

Country	Position	Share data	Use data	Impedes work	GSP
USA	PhD	100%	88%	25%	96%
	PostDoc	98%	67%	55%	98%
	Senior	100%	65%	53%	88%
UK	PhD	88%	66%	81%	59%
	PostDoc	80%	52%	72%	80%
	Senior	72%	52%	60%	76%
GER	PhD	72%	70%	72%	86%
	PostDoc	87%	59%	74%	89%
	Senior	94%	44%	67%	89%

Table 2.6: Attitudes towards data sharing by positions

Table 2.6 shows the heterogeneous effect of career stage on sharing between the different countries. In the United States, Postdocs use the least data shared by others (p=0.057 compared to PhD) and are the most likely to think mandatory sharing impedes their work (p=0.015 compared to PhD). This pattern is not found in the other two countries.

In contrast, German researchers' tendency towards sharing research data increases with their academic rank (p=0.081 comparing PhD to Postdoc, p=0.052 comparing PhD to Senior). At the same time, they indicate a decreasing use of data shared by others (p=0.063 comparing PhD to Senior).

As previously mentioned, we have also asked researchers about their opinions on when data should be shared. Figure 2.8 shows their answers broken down by countries and disciplines. As before, there are only minor differences between the disciplines, and the UK and Germany are fairly similar, while researchers in the United States show very different attitudes (p<0.001). While Europeans predominantly think data should be shared at the conclusion of the research project or some time after it, the respondents from the US would favor doing it much sooner, such as when it was collected or at the time of publication.

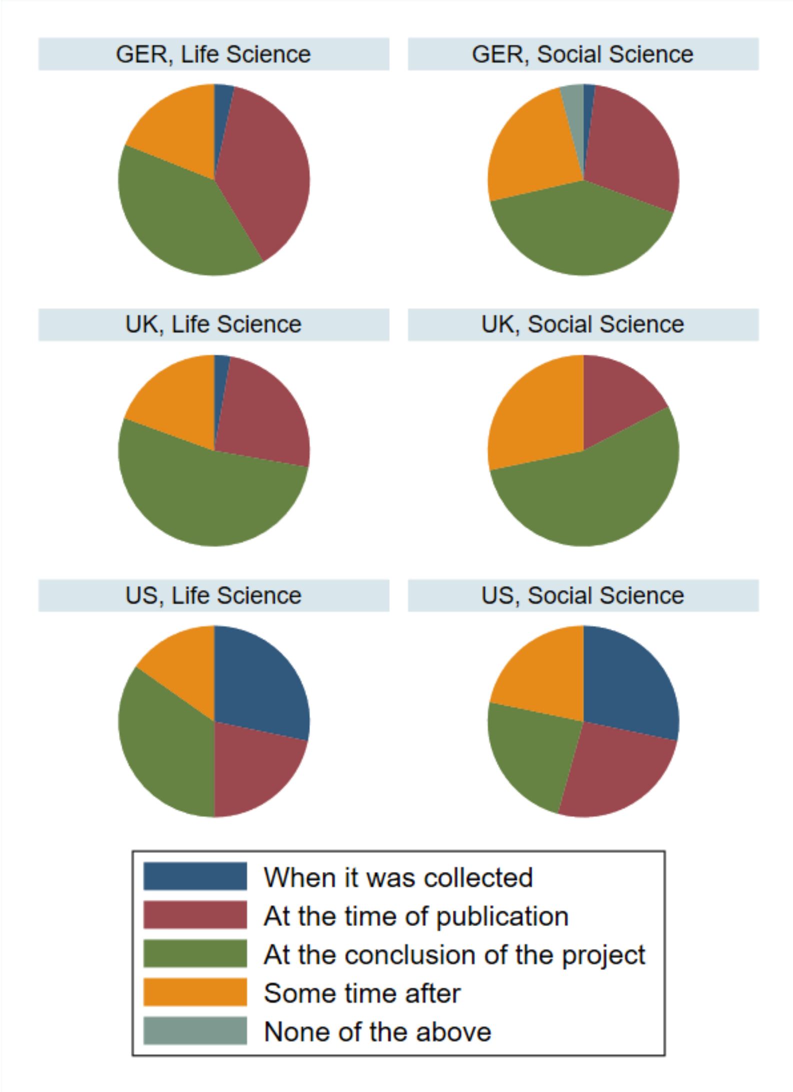

Figure 2.8: When should data be shared by country and discipline

Thus we can say that differences between the personal opinions of researchers regarding data sharing mainly stem from the country they work in and their level of seniority, while the discipline they work in only has a limited impact.

2.5 Limitations

Our survey-experiment offers intriguing insights; however, it is imperative to recognize its limitations. First and foremost, the sample is confined to volunteering participants from three countries: the United States, the United Kingdom, and Germany. Given the relatively small number of participants from each country, our sample is not representative for the entirety of their scientific communities. Furthermore, our recruitment method may have inadvertently biased our sample towards individuals with pronounced opinions on Open Science, potentially skewing results in favor of those more positively inclined towards the concept. Consequently, the attitudes reported in this survey should be considered indicative of a best-case scenario rather than reflective of the broader research community. Regardless, the results presented here should provide novel insight into the state of open data. The differences between countries should especially be highlighted, which indicate the importance of the regulatory environment.

Another limitation is our survey's exclusion of countries with substantial scientific contributions or advanced Open Science policies beyond the Western context, omitting a diverse global perspective on the issue. This Western-centric approach fails to capture the worldwide scope of Open Science and its implications across different scientific landscapes and therefore should be rectified with further research.

Moreover, the observed small variance in attitudes across disciplines suggests that our categorization into Life Sciences and Social Sciences may have been overly simplistic. This broad classification likely did not capture the intricate distinctions and specific attitudes inherent to the various sub-disciplines within these disciplines.

2.6 Conclusion

This study has examined the attitudes of researchers in the life sciences and social sciences from the United States, the United Kingdom, and Germany towards Open Science and data sharing. Our findings reveal that the country researchers work in significantly influences their research practices and attitudes towards data sharing. While researchers in the United Kingdom and Germany display relatively similar views, their counterparts in the United States demonstrate distinct differences, suggesting varying levels of Open Science and data sharing maturity across these regions. In Europe, there appears to be a more individualistic and less regulated approach to Open Science, with researchers more frequently sharing incomplete data, primarily being concerned about the time required for sharing, but still regarding it as good scientific practice, and viewing themselves as the main drivers of the data sharing process. Conversely, in the United States, the approach is more regulated and institutionalized, with a stronger emphasis on sharing complete data sets, greater concerns about data misuse and its impact on personal scientific interests, and a significant influence of institutional or funding body mandates on data sharing practices. Regarding the tightness and looseness of norms we predominantly find that social norms in this context are tighter in Europe and comparatively looser in the US. This is most likely explained by the US being more heterogeneous due to its size, but also being more progressive as a whole.

Our analysis indicates that the broadly categorized discipline of research has a negligible impact on attitudes toward data sharing, which could be due to our broad categorization in life sciences and social sciences, obscuring specific disciplinary nuances. It could also indicate that research culture is predominantly shaped by national context.

Regarding individual practices and opinions, a similar pattern to that in the vignettes emerged. U.S. researchers report higher rates of data sharing and usage, more frequently acknowledge its role in good scientific practice and are less likely to view mandatory sharing as an impediment to their work. The only notable difference across disciplines is that social science researchers are less likely to view mandatory data sharing as obstructive, possibly due to the nature of their data which may be inherently easier to share than in the life sciences.

Significant positional differences within countries also exist, with senior researchers in Germany more likely to share data and less likely to use others' data compared to their junior counterparts. In contrast, in the United States, postdoctoral researchers are less likely to use others' data and more likely to feel that sharing hinders their work compared to PhD students.

For future research, expanding the scope to include more countries, particularly those with a more developed culture of data sharing, is recommended. Additionally, investigating perceptions and practices in non-Western countries could offer insights into distinct social norms and challenges faced by researchers in these contexts, thereby enriching our understanding of global attitudes towards Open Science and data sharing.

3. Social norms and motivations regarding data

Authors

Leon Houf & Tamas Olah

Abstract

This study investigates public perceptions regarding the access and use of various types of personal data, focusing on who individuals believe should have access to this data and the motivations behind these entities' interest in it. Utilizing an international cohort, we recruited 853 participants from the following countries: the USA, the UK, Germany, the Netherlands, Poland, and Israel. Our methodological approach is inspired by Krupka and Weber (2013) with further refinements by Merguei, Strobel, and Vostroknutov (2022). Instead of soliciting personal opinions, we seek to understand how respondents perceive societal norms in their respective countries regarding data privacy.

Participants were queried on the appropriateness of access to personal data by different stakeholders, including governments, businesses, academics, health providers, and general practitioners, across various sources and for disparate purposes. Additionally, we explored the presumed motivations behind the desire of governments, businesses, and academics to access this data.

Our findings reveal nuanced preferences among participants regarding data sharing, attributing varied motivations to the different actors interested in accessing personal data. Attitudes are largely similar in all surveyed countries with regards to how they see the different actors and their possible motivations. Additionally, we find that Businesses and Governments are seen as very much alike, primarily being motivated by self-interest and participants rate it as not appropriate for them to access data in most cases. Meanwhile, Researchers are seen as more altruistic and, therefore more appropriate to share with.

Keywords

Social Norms, Data Sharing, Motivations, Personal Data

3.1 Introduction

The sharing and accessing of personal data by various stakeholders has emerged as a pivotal issue in contemporary society. On the one hand, personal data harbors the potential for significant benefits, such as driving technological innovations (Mayer-Schönberger & Ingelsson, 2018), enabling the personalization of medical treatments (Fröhlich et al., 2018), and enhancing the delivery of various services. Moreover, in the realm of commerce, it serves as a critical asset, underpinning the strategies of modern businesses. The importance of data has been further accentuated with the advent of artificial intelligence (AI). High-quality, large datasets are indispensable for the training of neural networks, which are at the heart of AI development, fueling advancements in machine learning and contributing to the acceleration of technological progress (Bessen, Impink, Reichensperger, & Seamans, 2021; Whang, Roh, Song, & Lee, 2021).

However, the collection and use of personal data is not without contention. Stringent legal frameworks, such as the General Data Protection Regulation (GDPR) in the European Union (European Parliament & Council of the European Union, n.d.), underscore the commitment to protecting individuals' privacy rights. These regulations reflect a growing public sentiment that seeks to limit access to personal information, emphasizing consent and transparency. Despite the legal protections, there remains a significant variance in perceptions and regulations across different nations and cultures regarding the extent and nature of data access (Custers, Dechesne, Sears, Tani, & Hof, 2017). This divergence is not only evident among countries but also among individuals within those countries, highlighting the complexity and sensitivity surrounding data privacy issues.

The debate over data privacy has been further complicated by specific instances, such as the requirements to show proof of COVID-19 vaccinations for accessing certain services or locations (Bardosh et al., 2022). The controversies surrounding the collection, storage, and use of such health data have illuminated the broader challenges of balancing public health concerns with individual privacy rights. These instances serve as poignant examples of the ongoing struggle to navigate the ethical, legal, and social implications of personal data usage in a way that respects individual privacy while harnessing the potential benefits for society at large.

For these reasons we have designed an exploratory survey to gain insight into how people think about their data. Due to the rapid changes in the field, we did not base our hypotheses on established theory and thus did not preregister our survey. Rather, our exploratory study aims to delve into the nuances of public attitudes towards the sharing and accessing of personal data. By exploring the perspectives of individuals from diverse backgrounds, we seek to contribute to a deeper understanding of the global discourse on data privacy, the ethical considerations at play, and the potential pathways towards reconciling the conflicting demands of privacy and progress.

As such, in this paper we wish to answer the following questions:

1. With whom are participants willing (or not) to share data?
2. Is there a difference in how different actors are perceived?
3. Do people from different countries view their data differently?

3.2 Survey Design

3.2.1 General Concept

Our survey was implemented using oTree (D. L. Chen et al., 2016). It was designed to explore social norms around personal data, utilizing the methodology of Krupka and Weber (2013) with enhancements by Merguei et al. (2022). This approach aimed to capture the collective societal perspective rather than individual beliefs. Participants were asked to gauge the appropriateness of actions related to personal data on a 0 to 100 scale. An important feature of our design was the incentivization mechanism, which aligned rewards with the participant's ability to match their assessment within a 10-point range of their compatriots‘ average score, with a +/- 5-point margin of error for broader consensus, except for 0-10 or 90-100 which were fixed even if participants got closer to the ”edges”. An introductory example task was included to familiarize participants with the survey mechanics and incentive system, ensuring accurate and reflective responses. This step was critical in enhancing data reliability by ensuring participants' understanding of the collective reasoning process behind their evaluations.

3.2.2 Respondents

To get a good overview of how different people think about their data, we used Prolific to recruit participants from a number of different countries. These countries were primarily selected for their economic and scientific contributions and distinct cultural characteristics (Hofstede, 1984, 2011; House, Hanges, Javidan, Dorfman, & Gupta, 2004).

Country	Observations
United States	150
United Kingdom	152
Germany	150
Netherlands	151
Poland	150
Israel	100

Table 3.1: Countries and number of observations

Overall we had 853 participants, Table 3.1 shows the exact countries surveyed and the number of observations in each. We requested a balanced sample gender-wise, therefore 49.47% of our subjects were female. The average age of our participants was 32.7 (SD=11.72). Nearly all of our subjects at least completed high school, and the vast majority had some form of university education.

3.2.3 Actors

In our survey, participants were prompted to evaluate the appropriateness of sharing various types of data with specific entities, including:

- Government
- Researchers
- Business
- Health Provider
- General Practitioner

To ensure uniformity in response and reduce potential biases, these entities were consistently presented to participants across all scenarios and in the same sequence. This methodological choice was based on the rationale that these actors are not only capable of utilizing personal data but also stand to significantly influence individuals and society based on how they handle such information. This approach allowed us to systematically gauge public sentiment on data sharing preferences, reflecting on the perceived trustworthiness and societal impact of each entity in the context of personal data utilization.

3.2.4 Motivations

We have also asked participants to indicate what may motivate these actors in their activities, such as:

- Benefiting themselves
- Benefiting those close to them
- Benefiting others
- Following the rules
- Breaking the rules
- Not wanting to be involved
- Not having another choice

These factors were also the same in all cases, and displayed in the same order to maintain consistency across the various situations. The set of possible motivations was compiled to be able to track and account for a wide range of potential motivations, based on a variety of different factors. It should allow for preferences for personal gain, in-group favouritism (Fu et al., 2012), altruism (Batson & Shaw, 1991; Schwartz & Howard, 1984), rule-following (Milgram, 1963), rule-breaking (Brehm, 1966), generally avoiding certain situations, or not having a choice to do otherwise.

3.2.5 Situations

As previously mentioned, we designed a number of different situations to investigate how people think about different kinds of data.

The situations came from the following domains:

- Medical Research
- Psychological Research
- Health Checkup
- Financial Data
- COVID-19 Vaccination
- Social Media

The vignettes concerning Medical and Psychological Research asked how people feel about data generated for research purposes being shared outside of the scope of the original research, without explicit consent from the research subjects. Related to these two is data generated from routine Health Checkups, where we explained that the person in question does not have any health issues, but the mentioned actors are interested in the data generated from a routine checkup. Still in the health domain, we also inquired about data regarding the COVID-19 vaccination status of people, being vaccinated or not, and the type of the vaccine used.

Financial Data covers salaries, purchases, and general information connected to one's bank account. This is something that people consider to be relatively sensitive, but in practice is routinely used for advertising purposes, and technically banks have full access to it.

Social Media refers to data shared by a person on different platforms online, covering personal messages, interests and opinions on different subjects. In practice, this kind of data is also very often accessed by others, such as companies, but we expect participants to be quite averse to it.

3.3 Results

3.3.1 Appropriateness of Data Sharing

By actor - over all domains and countries

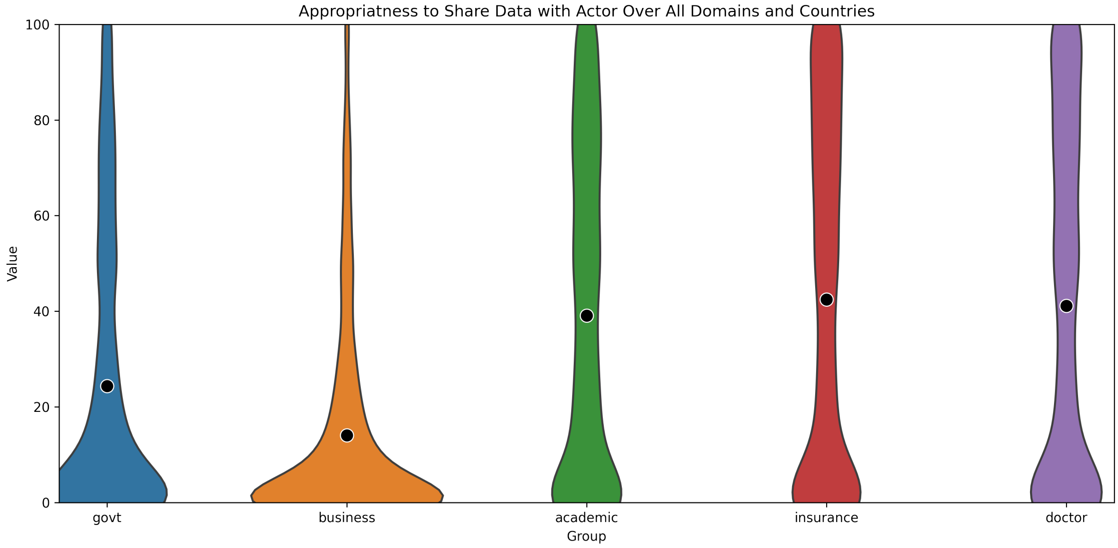

Figure 3.1: Appropriateness to Share Data with the Actors

Figure 3.1 shows how appropriate it is for the listed actors to get access to data combining all countries and situations. Our analysis reveals a clear dichotomy in perceptions: governments and businesses are viewed similarly and elicit the least willingness from participants to share their data. On the other end of the spectrum, academics, doctors, and health providers are grouped together as entities with whom subjects are comparatively more open to sharing their information. However, it is critical to note the diversity in opinions regarding these latter three actors; despite a general inclination to share data with them, responses vary widely, spanning the entire spectrum of willingness to share.

By domain - across actors and countries

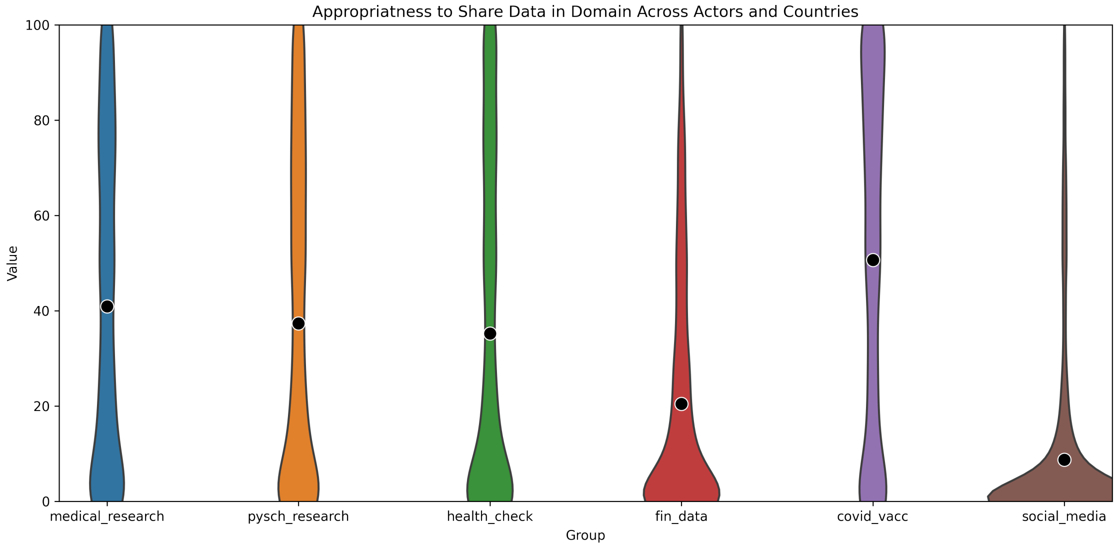

Figure 3.2: Appropriateness to Share Data by Domains

Figure 3.2 illustrates the overall willingness of participants to share data across different domains with various actors. Notably, there's a pronounced willingness to share data related to Medical and Psychological Research. Meanwhile, the readiness to share data from Health Checkups is significantly lower, despite the similarity in the actual information it holds. This distinction underscores the importance of the data's genesis; participants differentiate between data based on its origin and purpose, indicating that the context in which data is generated significantly influences sharing preferences.

The data on COVID-19 vaccination status stands out due to the high average willingness to share, with responses distributed broadly across the spectrum. This finding is particularly intriguing given the extensive public discourse surrounding the topic. Sharing this type of data with the government shows a perfect median willingness score of 50%, yet beneath this average lies a deep polarization: 21.78% of participants deemed sharing this information with the government as highly inappropriate (10% or less), whereas 16.39% found it highly appropriate (90% or more), as detailed in Figure 3.3. This polarization contrasts with the more uniform views regarding sharing vaccination data with other actors.

In stark contrast, participants expressed a significant reluctance to share financial and social media data. They view these as much less acceptable for sharing, despite the fact that such information is routinely accessed and utilized by companies and, in some cases, by governments. Social media data in particular is considered highly private, a sentiment that sharply contrasts with its frequent use and sharing in reality.

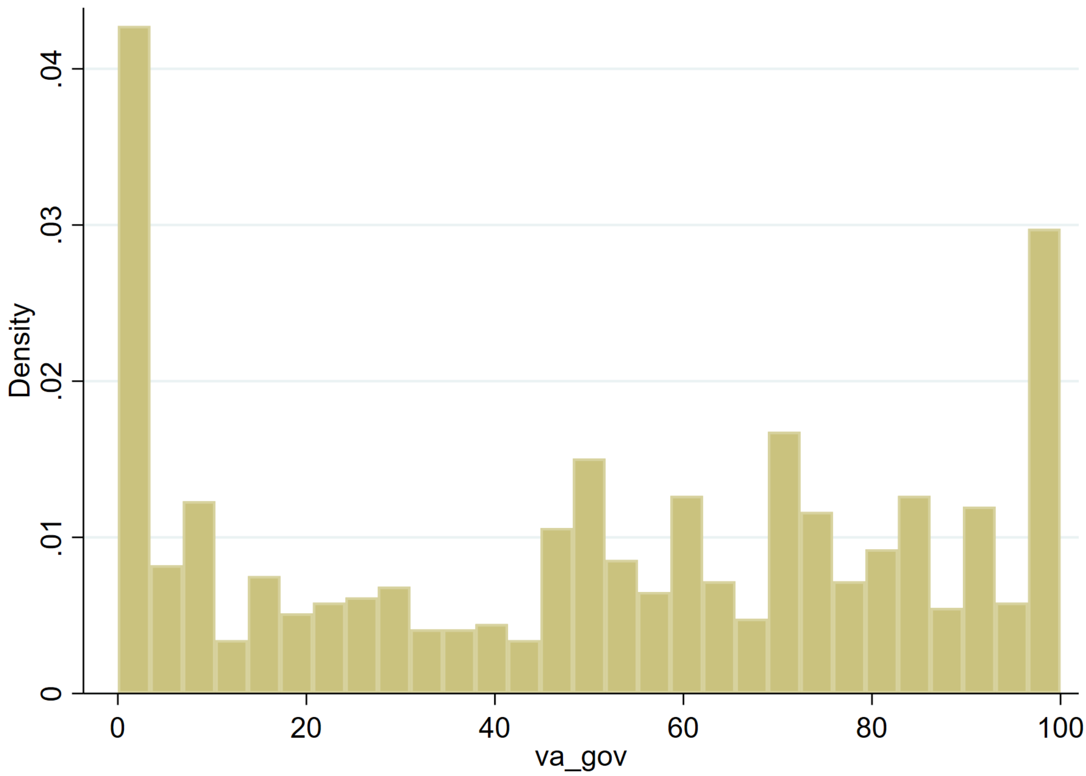

Figure 3.3: Sharing COVID Vaccination data with Government

By country

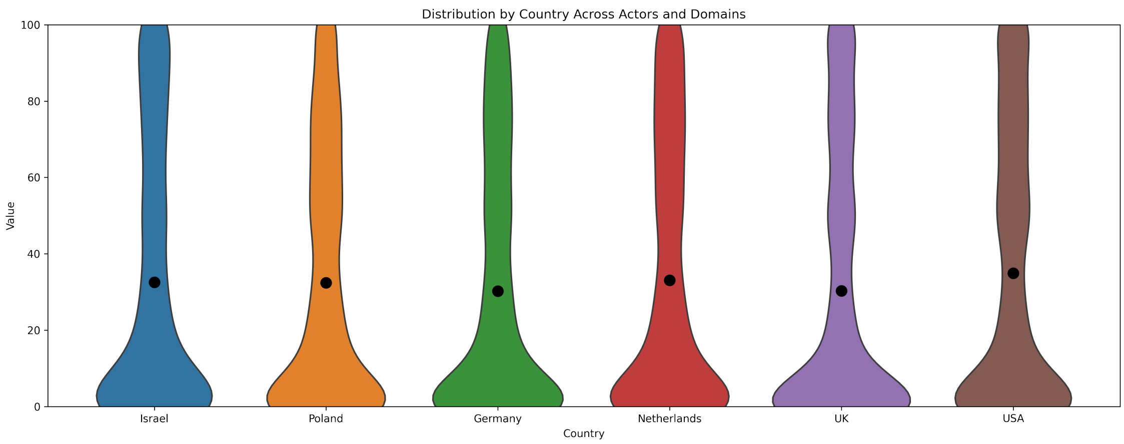

Figure 3.4: Overall willingness to share by Country

Figure 3.4 shows the point allocation by country. All the countries investigated behave very similarly. This goes against our baseline expectation, and it is difficult to pinpoint the underlying causes for it, as it might just be that combining all actors and situations could mask individual differences. That being said, this highlights that all countries more or less agree on most of the rank orders of appropriateness as shown previously. On the other hand, this also reinforces our findings by showing that the surveyed norms are commonly shared by people across countries and cultures.

Actors by country adjusted by country mean

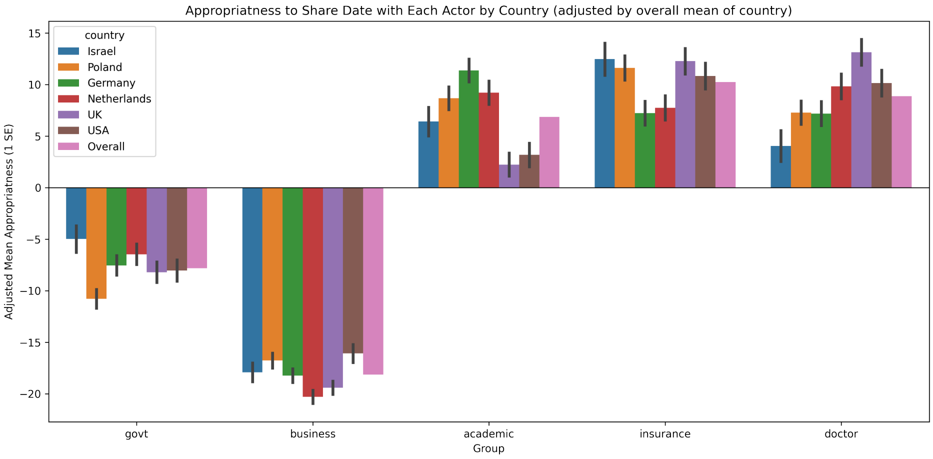

Figure 3.5: Sharing with the different Actors by country adjusted by country mean

Figure 3.5 provides a nuanced view of the willingness to share personal data with different actors, adjusted by normalizing the responses against the average scores for each country. This adjustment allows for a direct comparison of preferences across countries, relative to each country's baseline willingness to share data. In this analysis, governments and businesses consistently rank below the average in terms of perceived appropriateness for data sharing, indicating a general skepticism towards these entities across the board. In contrast, researchers, health providers, and doctors are viewed far more favorably, positioned above the average willingness to share data in all the countries surveyed.

Although the exact rank order of actors varies slightly from one country to another, the overall trends remain strikingly similar. This again suggests a broadly shared set of values and concerns regarding data privacy and trust in different actors. However, notable exceptions emerge, particularly in the context of sharing data with researchers. Countries in the European Union, with Germany as a prominent example, demonstrate a high level of openness to sharing data with researchers, possibly reflecting a strong trust in academic institutions and a value placed on research for societal benefits. Conversely, the United Kingdom and the United States exhibit comparatively lower levels of appropriateness assigned to sharing data with researchers, indicating a more cautious or reserved stance toward academic data use. Israel represents a middle ground, reflecting attitudes that are neither as open as those in the EU nor as reserved as those in Anglo countries.

This variation highlights the influence of cultural, legal, and possibly historical factors on public attitudes toward data sharing with researchers. The differences suggest that while global trends in data privacy concerns are evident, specific attitudes towards certain actors like researchers can be significantly shaped by the national context. This insight into the differential trust levels towards researchers across countries underscores the importance of considering cultural and national nuances when developing policies or strategies for data sharing and privacy.

3.3.2 Motives to Access Data

Figures 3.6, 3.7, and 3.8 show the ascribed motivations for why a certain actor would want to access data. We find that businesses and governments are overall seen similarly, but our respondents think about researchers in a very different way.

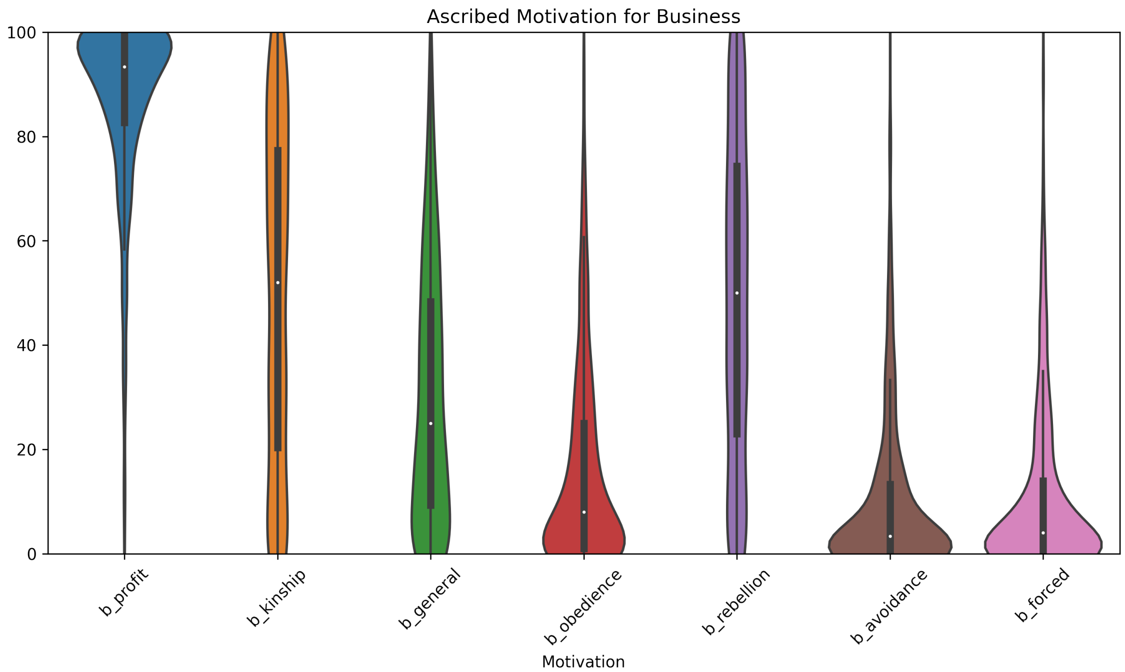

Figure 3.6: Motivations of Businesses

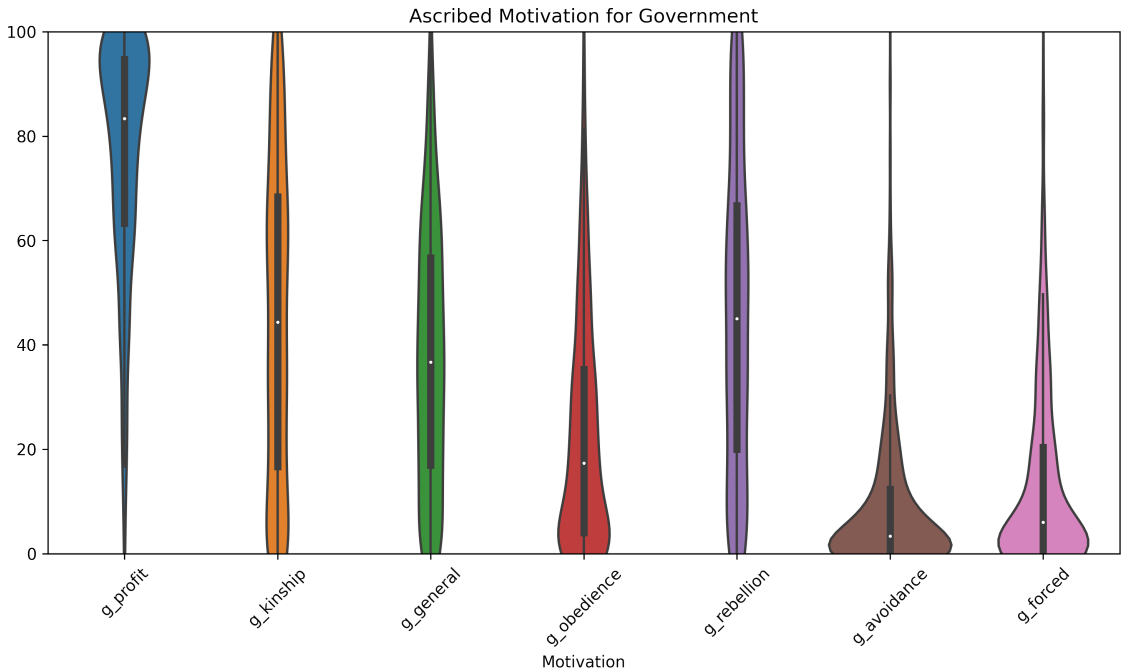

Figure 3.7: Motivations of Government

Our findings suggest that public perceptions of the motivations of businesses and governments to access data lean heavily toward self-interest. Participants commonly view these entities as primarily driven by the pursuit of personal profit (profit) or, at best, the interests of their specific in-group (kinship). This perspective is coupled with skepticism towards their adherence to regulatory and ethical standards (obedience), with both businesses and governments frequently perceived as more likely to circumvent or outright break rules in their handling of personal data (rebellion). Moreover, there is little belief that these actions are taken under duress (forced) or as a means of preventing further hardship (avoidance), indicating a perception of deliberate choice rather than compulsion in their approach to data access.

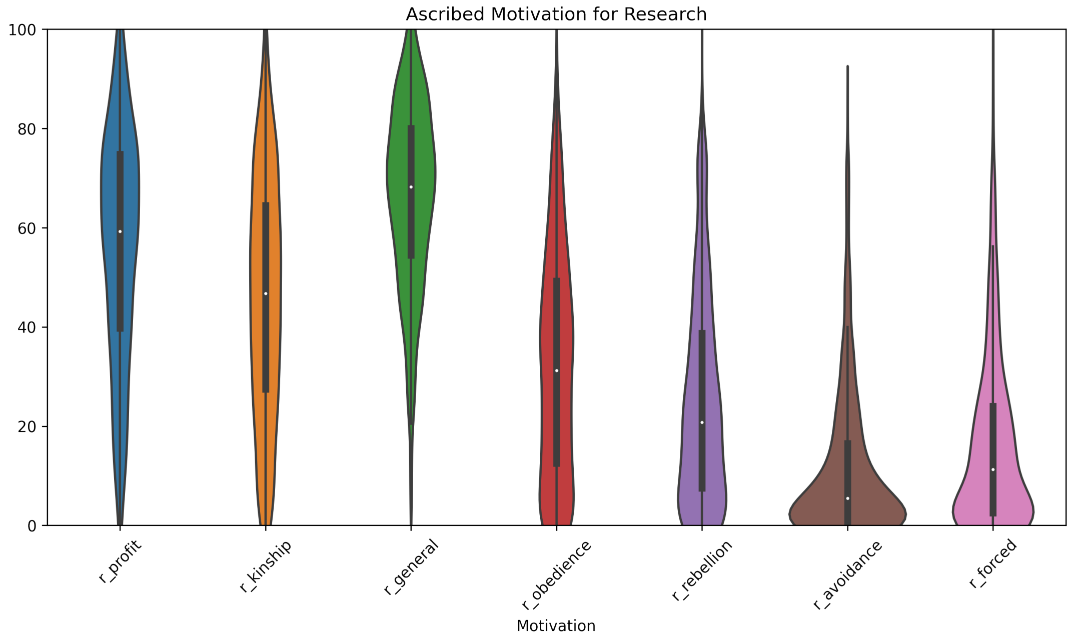

Figure 3.8: Motivations of Researchers

In contrast, researchers are perceived in a more favorable light. The public sees their motivations as fundamentally oriented towards the benefit of others (general), with a secondary consideration for self or in-group benefit. This altruistic perception is supported by a belief in researchers' greater likelihood to comply with rules and ethical guidelines across various data access scenarios. Unlike businesses and governments, researchers are not viewed as being driven by a desire to avoid negative outcomes or acting out of necessity. Instead, their motivations are seen as more principled and voluntary, reflecting a commitment to advancing knowledge and societal welfare.

These distinctions in perceived motivations highlight significant differences in public trust and expectations regarding the behavior of different actors in the realm of data access and usage. While businesses and governments are approached with caution and skepticism, researchers are given a degree of trust, possibly based on the belief in their commitment to the greater good and adherence to ethical standards. This divergence underscores the importance of transparency, accountability, and ethical conduct in maintaining or improving public trust in entities that handle personal data.

3.4 Limitations

This study was primarily exploratory in nature, thus lacking a foundational theoretical framework. Its aim was to uncover general norms and motivations within the realm of personal data usage and sharing. However, the scope of situations, actors, and potential motivations examined was necessarily restricted, leading to a potential loss of nuance in these areas. Although the survey encompassed participants from a diverse array of countries, it was constrained by platform limitations, resulting in a notable lack of non-Western countries. Additionally, despite achieving a gender-balanced participant pool, the sample was not representative of the whole populations and may not accurately reflect their beliefs.

Given these constraints, future research should prioritize expanding the geographical focus to include a more diverse range of countries, with an emphasis on non-Western contexts. This would allow for a more comprehensive examination of the stability of norms across different cultural landscapes. Moreover, there is a need to broaden the range of situations and actors considered in the study to more fully capture the variety of interactions individuals have concerning personal data.

3.5 Conclusion

In this study, we delved into the injunctive social norms surrounding the sharing of personal data across various countries, focusing on public perceptions of the motivations behind different actors' interest in accessing this data. Our survey was highly exploratory and aimed to provide some overall insights in the fast-moving domain of the sharing and use of data. Our findings reveal consistent trends across the surveyed nations, shedding light on the entities with whom individuals are most and least willing to share their personal information, as well as the underlying reasons for these preferences.

We find remarkable stability in preferences across the surveyed countries with regard to whom participants rate to be appropriate to share with, as well as the perceived motivations behind these actors. Our analysis indicates a general willingness among participants to share data with researchers, particularly in the medical and health domains, where health providers and doctors are also considered trustworthy recipients. This openness contrasts sharply with the marked reluctance to share data with governments or businesses. The sensitivity of the data and its intended use emerged as critical factors influencing willingness to share; the further the data's use strays from research purposes, the less inclined individuals are to share it. Notably, participants were relatively comfortable sharing medical research data with researchers outside the original study's scope and with health professionals, highlighting the perceived importance of the purpose for the data's original generation. Sharing COVID-19 vaccination status was deemed acceptable with medical professionals and researchers, and to a lesser extent with the government, though opinions varied on this matter. In stark contrast, sharing financial details or social media activity was widely viewed as inappropriate. Curiously, in the real world, these types of data are the ones that are most commonly shared, mainly across different businesses. Thus, our survey highlights the importance of data protection and the need for regulation.

The study also uncovered distinct perceptions of businesses, governments, and researchers. Researchers were viewed in a positive light, perceived as altruistic and motivated by a desire to contribute to societal welfare and adhere to ethical standards. Conversely, businesses were primarily seen as self-interested entities focused on profit, often at the expense of ethical considerations. The government's perception fell between these two, leaning more towards the business end of the spectrum, with motivations attributed to personal gain but also to a degree of societal benefit.

These findings underscore the complex landscape of data privacy and sharing preferences, reflecting the nuanced motivations and trustworthiness of various data handlers. They suggest a critical need for transparent, ethical data handling practices, especially by businesses and governments, to align more closely with the public's expectations and social norms. Further, the results highlight the importance of the data's intended use and origin in shaping sharing preferences, offering insights for policymakers, researchers, and practitioners in navigating the ethical dimensions of data use and privacy.

4. Data Sharing in Science: The Principal - Agent relationship between Researchers, Research Institutions and Funding Agencies

Authors

Tamas Olah & Christiane Schwieren

Abstract

Data is taking a focal importance in our world across a variety of domains. Research data is said to unlock numerous societal benefits if made available to other researchers for further exploration (Tenopir et al., 2011, 2015). To better understand how data sharing works in practice and to help design systems that can benefit all stakeholders, we conducted an experiment to examine the relationship between Researchers, Research Institutions, and Funding Agencies. These three agents have different incentives, capabilities, and goals, but must work together to produce scientific research.

We find that small changes in incentives, or small punishment threats in case of non-compliance with sharing proposals have no significant effect on the Researchers' data sharing behavior. Researchers are generally willing to share data but are limited in their ability to do so by having to use the very same resources that are also used for conducting research, both in our experiment as in real life. This leads to a conflict of interest as publishing has far more individual benefits compared to data sharing. Therefore Researchers generally fulfill minimum sharing requirements but do not go much above it if they feel that they are constrained.

We also find that participants playing the role of Research Institutions do for the most part monitor and punish Researchers if they do not comply with their funding proposals. This is affected by the Researchers' general performance, where high-performing ones are treated differently from low-performing ones.

Keywords

Open Science, Data Sharing, Principal-Agent, Academia

4.1 Introduction

The practice of sharing and reusing research data has become a central and contentious topic in the scientific arena. Advocates of the Open Data movement argue that data sharing offers a spectrum of advantages, including the cost and time efficiency of scientific research by maximizing the impact of data. Furthermore, an argument could be made for the efficient use of limited research funds. Funding agencies are urged to avoid redundant data collection, thereby optimizing resource allocation (Pronk, 2019; Tedersoo et al., 2021). Data sharing is also championed as a means to promote transparency, potentially resolving the replication crisis plaguing various disciplines (Munafò et al., 2017; Warren, 2016).

Despite the apparent benefits, the current practice of data sharing is fraught with challenges. Researchers often find that the additional workload required for data sharing is undervalued in career advancement, as compared to publications (Fecher et al., 2015; Tenopir et al., 2011). Funding agencies typically mandate data sharing in grant proposals, often through data management plans (Wendelborn et al., 2023; Williams, Bagwell, & Zozus, 2017), creating a dilemma in researchers' priorities. On the one hand, researchers have clear personal benefits from producing publishable results, and on the other hand, they face the less tangible benefits of data sharing (Sayogo & Pardo, 2013), which still are a necessary aspect of grant applications, but are rarely controlled for or enforced. Research institutions also face a dilemma: they do not derive the same direct benefits from their researchers' data sharing efforts as they do from traditional scientific outputs, i.e., publications.

This situation creates a tripartite principal-agent relationship with misaligned incentives, wherein research institutions act both as principals (to researchers) and as agents (to funding agencies). The dynamics of data sharing thus involve a complex interplay between researchers, research institutions, and funding agencies. Each entity has distinct interests yet has to collaborate with the others, which leaves room for sub-optimal outcomes, overall and for each entity. Funding agencies often drive data sharing initiatives, with researchers being responsible for the implementation. Research institutions, meanwhile, play a crucial role in facilitating data sharing and enforcing related policies (Anger et al., 2022). Next to (so far scarce and weak) extrinsic incentives, data sharing in real-world settings is based mostly on intrinsic motivation.

This suggests the need for an institutional design that aligns the interests of researchers, institutions, and funding agencies. Such a design should not only recognize and reward the efforts involved in data sharing but also address the structural and policy-related barriers that currently impede its effectiveness. Developing a system that integrates data sharing as a valuable component of scientific contribution, both in terms of career advancement and institutional recognition, could significantly mitigate these challenges. Laboratory experiments can be used as test beds for new institutional designs, so we designed an experiment to trial a set of possible changes in the current incentive structure. We start with a baseline mirroring the existing incentive structures and make changes to investigate the effects of more thoroughly enforcing existing policies, or providing direct rewards for sharing. These interventions are meant to be salient, but still rather small, as bolder incentives are not probable in the real-world setting we want to imitate.

The remainder of the paper is structured as follows: the next section will provide an overview of the relevant literature. The third section describes our approach, including a basic model and an extensive description of the procedures of the experiment. Section four describes the results, and section five summarizes the findings.

4.2 Method

4.2.1 Principal-Agent scheme

We model the scientific landscape as a principal-agent problem (Anger et al., 2022; Braun & Guston, 2003), simplifying the real-world setting, but keeping its main aspects. The setting consists of two interconnected principal-agent (PA) relationships: Researchers are the agents, with Research Institutions as their principals. However, they both get funded by a Funding Agency, with whom they thus also have a PA relationship. Research Institutions have a PA relationship as agents with the Funding Agency as principal, who funds them, and to whom they report whether Researchers (their agents) behave according to their promises. They are thus Principals to the Researchers, but Agents in relation to the Funding Institution (see Figure 4.1).

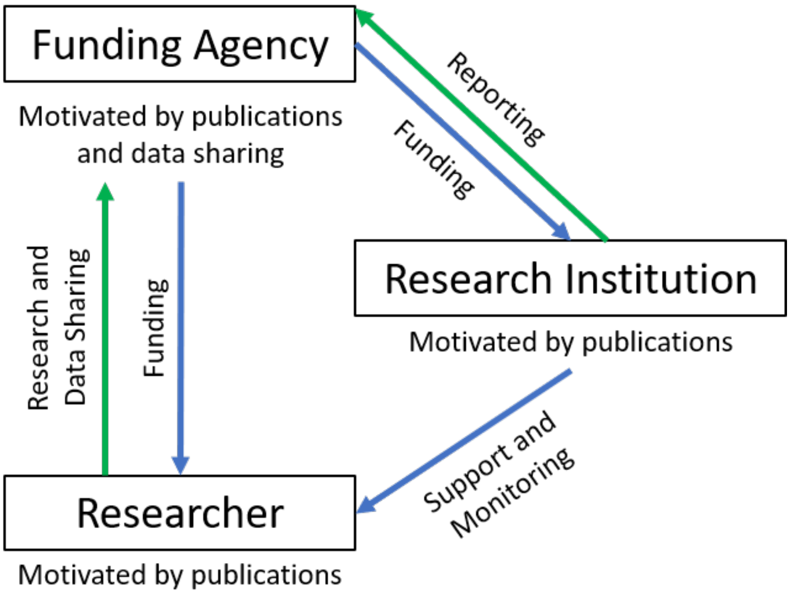

Figure 4.1: Relationships between the different actors

We describe each role´s tasks and incentives in the following:

Researchers generate two types of output: publications and data (that can be shared). They get paid for their publication output. To generate that output, they need money, which they get from the Funding Agency. To gain funding, Researchers have to make promises on how many papers they will write and how much data they will share. It is possible for them to fail to fulfill their promises or not follow through on purpose.

Research institutions also generate two types of output: Support for Researchers and Monitoring of Researchers, i.e., information on whether Researchers accomplished their goals. They get paid for their Researchers' publication output.

Funding Agencies fund Researchers and Research Institutions and Monitor and Punish Researchers´ behavior.

The focus of the monitoring and punishment is on deviations of Researchers with respect to the output they promised, both in terms of data sharing and publications. The core of the PA relationship with misaligned incentives is that Researchers can deviate from their proposals to maximize their payoffs. Research Institutions can punish Researchers, but their incentives imply that ignoring Researcher misbehavior is optimal, especially if Researchers have high publication output and misbehavior is about data sharing. Researchers and Research Institutions thus have an incentive to collude against the interests of the Funding Agency.

4.2.2 Procedures

The experiment was administered in person in the lab of Heidelberg University and was coded with oTree (D. L. Chen et al., 2016). The whole experiment took about 45 minutes to complete, a large part of which (approximately 15-20 minutes) was spent on making sure that participants understood the instructions. Due to the complexity of the experiment, we used several procedures to ensure understanding, such as control questions and a practice round, as well as the instructions being available for reference at any time during the experiment. When participants entered the lab, they were randomly assigned to groups of two, one participant playing the role of a Researcher and the other the role of the Research Institution. The behavior of the Funding Agency was automated and varied depending on the treatment. This was known to all participants. In all treatments, participants' payoffs mainly depended on the Researcher's publication performance, while data sharing had no direct effect on payoffs. This mirrors the real-world situation, where data sharing still carries little to no direct individual rewards. The treatments then varied the indirect cost or advantages of (not) sharing data, by increasing detection probability or providing some small but tangible reward for sharing.

In general, Researchers decided how to allocate their resources between working on publications or sharing data. They first had to submit a proposal to the Funding Agency concerning both data sharing and publications, but could later deviate from this to maximize their payoffs. In the first period, Researchers got a predefined amount of resources to allocate between data sharing and publications, subject to feasibility restrictions. The amount of resources in later rounds depended mainly on publication success in earlier rounds. Resources allocated to publications led to publications with a specified probability of success. Data sharing happened with certainty, but only if enough publications had been achieved. Data sharing was not payoff-relevant in itself, only indirectly through possible punishment if it was not carried out as promised.

Research institutions decided on how to support their Researchers as well as whether to monitor and punish them on behalf of the Funding Agency in case of non-compliance with their grant proposals. It was made clear to them that the Funding Agency expects them to report noncompliance, but they could also deviate to maximize their payoffs, as their final payoff also chiefly depends on their Researcher's publication performance.

From the second period, researchers were assigned to either the high group or the low group, depending on the number of publications they achieved in the first period, and the proposal they made for their output for the turn. This determined high or low funding and thus affected their chances of making further publications in the next round.

If Researchers did not fulfill their promises and the Funding Agency found out about this noncompliance, they (alongside their Research Institution) were banned from play in the following period.

4.2.3 Subjects

We recruited 170 participants from the subject pool of Heidelberg University. In the case of Researchers, the average age was 21.92941 (SD=6.423151), with 42.35% being women. As for the Research Institutions, the average age was 22.23529 (SD=5.478632), and 45.88% were women. The overwhelming majority of the participants were bachelor's and master's students. In this specific case, a student sample, especially containing master's students, comes relatively close to our target population of researchers and thus does not pose larger issues of external validity. Optimally, the sample would have consisted only of (young) researchers, but this is not feasible if aiming for a large sample size, and not absolutely necessary for a focus on incentive structures.

4.2.4 Treatments

Our treatments reflected the status quo as described above, with differences in competition for funding between the researchers, and two possible changes with respect to monitoring and punishment. The latter were designed so that they were small enough to be feasible as policy advice, and possibly strong enough to change behavior. Thus, our design is a two-by-three design, as we are applying all treatments for both levels of competition.

For the different levels of competition, we created a ”High Group” and a ”Low Group”, which Researchers could end up in. The High Group had more resources to spend, thus, Researchers aimed to be part of this group. We then varied the amount of publications necessary per round to be assigned to it. These expectations were explained in the instructions as well as shown with calculations in each round. In the first setting, three publications were expected per round, which was quite easily achievable and accordingly, pairs were in the High Group in 73.75% of cases. In setting two, four publications were expected per period, which was still feasible, but considerably more difficult, and accordingly pairs were in the High Group only 42.65% of cases.

In the treatments, we compared a set of potential interventions designed to incentivize data sharing. First, we ran a ”Baseline” treatment where subjects had no direct incentives for sharing data, which mostly approximates the real-world conditions (Anger et al., 2022). Second, we had a ”Carrots” treatment, where sharing data added a relatively small amount to researchers' final payoffs (1/10 the worth of publications), thus giving a salient and direct incentive to share. Thirdly, we ran a ”Sticks” treatment where the Funding Agency had a small (10%) chance to detect noncompliance with the data sharing proposals besides detecting noncompliance with the publication proposals. The logic behind

Publication Pressure	Treatment	Participants
3	Baseline	44
3	Carrots	38
3	Sticks	28
4	Baseline	24
4	Carrots	18
4	Sticks	18

Table 4.1: Treatments

this was that even though Funding Agencies currently avoid monitoring compliance with data sharing proposals for various reasons, this could potentially be improved. Due to resource constraints (in the real-world setting) a high level of monitoring is unlikely to be implemented, thus we were curious whether a small probability of monitoring had an effect already. The punishment was implemented automatically if monitoring had taken place and deviations had been detected (one period of no play).

4.2.5 Experimental Procedures

The sequence participants had to go through in each round was the following: First, the Researchers had to submit a grant proposal to the Funding Agency, including the promise of a certain number of publications and some amount of data sharing (minimum 2 data points, only possible with publications). The Funding Agency evaluated this proposal alongside the Researcher's publication history and compared it to a preset performance standard. The procedure in the first round differed from this, as no past performance was available yet. Thus, in the first period, each Researcher received the same amount of funding to start with.

To be considered successful (and thus, be allocated High funding in the next round) by the Funding Agency the Researcher had to fulfill the following criteria:

$$PastPub + ProposedPub + 0.2 * ProposedDS > FA'sExpectation * RoundNumber$$

Using this equation, the Funding Agency automatically assigned Researchers to the High group, granting them 12 tokens, or the Low group, giving them 8 tokens to use in the next period for both publishing and data sharing. Researchers were told that the Funding Agency expects them to follow through on their proposal. Since the Funding Agency's expectation is multiplied by the period number, it gets increasingly difficult to get into the High group in later periods. The Funding Agency can always detect noncompliance with the publication proposal, and, depending on the treatment, has a small chance of finding noncompliance with the data sharing proposal.

In the next step, the participants playing the Research Institution had to decide how to use their resources to support the Researcher they were paired with. The Research Institution had a fixed amount of tokens for supporting their Researchers in each round, plus some budget from the Funding Agency, depending on the Researcher's publication performance in the previous rounds. Each token spent on research support granted the researcher +1% probability to successfully publish, and each token spent on data sharing support gave 0.5% probability to successfully publish. The Research Institution had to assign at least as many points to data sharing support as the Researcher proposed to share.

Once the Researchers had received their tokens, they had to allocate them to publications and data sharing. Each point spent on publications had a baseline 50% chance to succeed. The extra odds resulting from the Research Institutions' support decisions were added to that. Each point spent on data sharing was sure to yield one point of shared data, but it was not possible to share more data than publications achieved. Participants thus were mechanically prevented from promising more data sharing than publications. If a lack of publications due to bad luck made it impossible to implement data sharing, the software chose the closest possible amount of data sharing, to avoid waste of resources.

In the next step, the Research Institutions were notified of their Researcher's performance in the current round and also reminded of the promises made by the Researchers in the first stage. If the outcome did not meet the promise, the Research Institution could choose what to do:

- They could Overlook the noncompliance, meaning not taking any action against the Researcher for not following the proposal.
- They could Punish the Researcher by taking the Researcher´s payoff from that round for themselves.
- They could Report the noncompliance to the Funding Agency, with the consequence of the Researcher (and thus, the institution) being banned from the next period. The Institution would get the tokens equal to the Funding Agency's Expectation (the Publication Pressure) added to their payoff.

In case of non-compliance with the publication proposal, the Funding Agency would find out regardless of the decision made by the Research Institution, which meant that players would be banned from the next period. In such cases, the Institution only received some payoff if they Reported the Researcher. In case of non-compliance with the data sharing proposal, the Funding Agency had no chance of finding out in all but the "Stick" treatments, in which it had a 10% chance to find out.

At the end of each round, participants were informed of everything that had happened in that round: the proposal, how many publications the Researcher made, and how much data they shared, and what decision the Research Institution made.

To reiterate, due to the complexity of this design, we broke the instructions into role-related parts as well as giving a general overview, asked a set of control questions to check comprehension, and had a practice round in the beginning. There was detailed information about the mechanics behind any given part on each page of the experiment. Participants also had the opportunity to check the instructions any time during the experiment again, by simply clicking on a tab.

We used neutral wording as much as possible and did not emphasize the prosocial aspect of sharing. We highlighted that Researchers were not forced by the software to follow through on their proposals.

To summarize the sequence of each round:

- Researchers submit a proposal to the Funding Agency promising a number of publications and an amount of data to be shared. Researchers are assigned to either the High or Low group accordingly.
- Research Institutions decide how to allocate their resources to support the Researcher assigned to them in publishing or data sharing.
- Researchers decide how to allocate the resources given to them by the Funding Agency. They can deviate from their proposals.
- Research Institutions see how the Researchers performed in that period and make their monitoring decision in case the Researcher did not comply with the proposals made.
- All participants see what happened in that round.

The experiment was played for several periods. Participants did not know how many periods the experiment would last, except that five periods would be played with certainty. After the five rounds, the experiment had a 33% chance of ending in each round, which the participants were informed of. This was implemented to avoid an end-effect and make the behavior of participants more consistent over time. After the last round, participants were informed about their final earnings, and directed to another page to fill out a form to facilitate their payments.

4.2.6 Optimal Play

Before discussing the results, the optimal strategy for the experiment will be considered. Due to the complex principal-agent relationship, this is not simple to determine, but we can theorize how a rational player should behave.

Since both the Researchers' and Research Institutions' payoff chiefly depends on the publication performance, a rational actor would maximize publications and generally disregard data sharing as much as possible. In the "Carrots" treatment, data sharing also provided some additional payoff, but only 1/10 of the worth of publications. Thus, it is still dominated by the rewards for publishing. With the monitoring decision, the Research Institutions were also able to increase their payoffs by Punishing or Reporting the Researcher in case of non-compliance. Doing so with respect to non-compliance with data sharing would push the Researcher to spend more on sharing instead of publications, which in turn would lead to lower payoffs in the long term for both the Researcher and the Research Institution. Since the number of periods for which the experiment would be running was not predetermined, it was not possible for players to opportunistically change behavior in the last round. In the "Sticks" treatment the Funding Agency had a small chance to detect noncompliance in the case of data sharing, but the chance was very low (10%), and thus should not have a large effect on behavior. For the Researchers, the most important consideration, in general, was belonging to the High group. This means they had to fulfill the Funding Agency's expectations, based (mainly) on publications. Rational Researchers should also not make unrealistic proposals that they could not fulfill regarding publications, because that would lead to missed rounds.

Thus in all treatments, the optimal play would be for Researchers to propose as little as possible (of both publication and data sharing), while still staying in the High group, thus minimizing the risk of noncompliance and thus missing a round. Following this logic, Research Institutions should spend as much of their budget on publication support as possible to maximize the Researcher's chance of gaining publications. In the next step, Researchers should not comply with their data sharing proposals, but spend all of their resources on publications. Lastly, Research Institutions should overlook this noncompliance, since it is also in their own best interest. Since the number of periods was not predetermined, it should be expected that this behavior continues throughout, without breaking down. Thus, collusion against the stated interests of the Funding Agency would maximize the payoffs of both players. Participants know that while Researchers and Research Institutions are played by real people the Funding Agency is automated. Thus, social preferences should also not play a role in the relationship with the Funding Agency.

4.3 Results

4.3.1 Researchers

Participants playing the role of Researchers predominantly do not behave optimally at any stage in the experiment as they do not maximize publications above all else.

The mandatory proposal of 2 points of sharing constitutes a focal point for participants. It is proposed in 52.08% and implemented in 44.58% of cases. As previously discussed, rational behavior would suggest that Researchers propose minimal sharing, and then do not comply with their proposals but spend all their resources on publications. Contrasting this, participants not only often propose higher than minimum sharing, but overwhelmingly spend at least the minimum amount or more on data sharing, and barely ever spend less (Figure 4.2). Thus, we can say that participants are not maximizing their payoffs by avoiding data sharing.

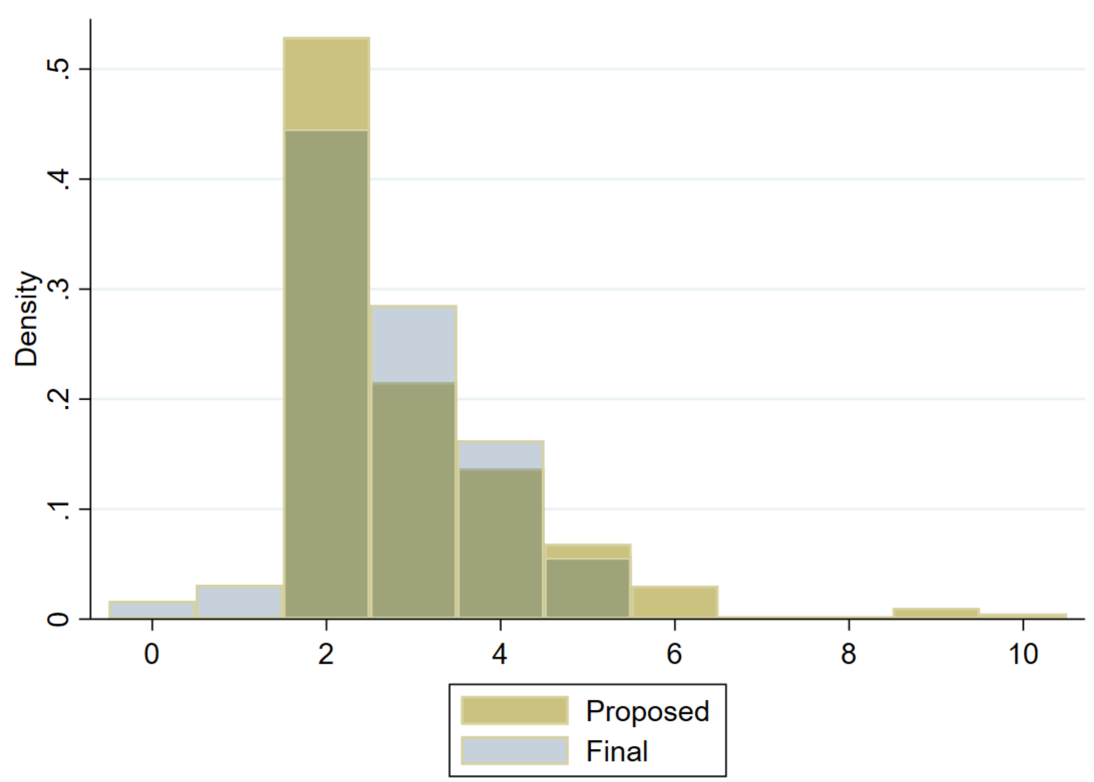

Figure 4.2: Data Sharing

Surprisingly, we find no fundamental difference regarding data sharing between the different treatments, nor do they differ with regard to publication behavior. This suggests that smaller (realistic) interventions by the Funding Agencies are not sufficient to affect the behavior of Researchers. On the other hand, the fact that the minimal proposal of 2 points is predominantly followed through highlights the importance of minimum requirements as (probably) heuristic defaults.

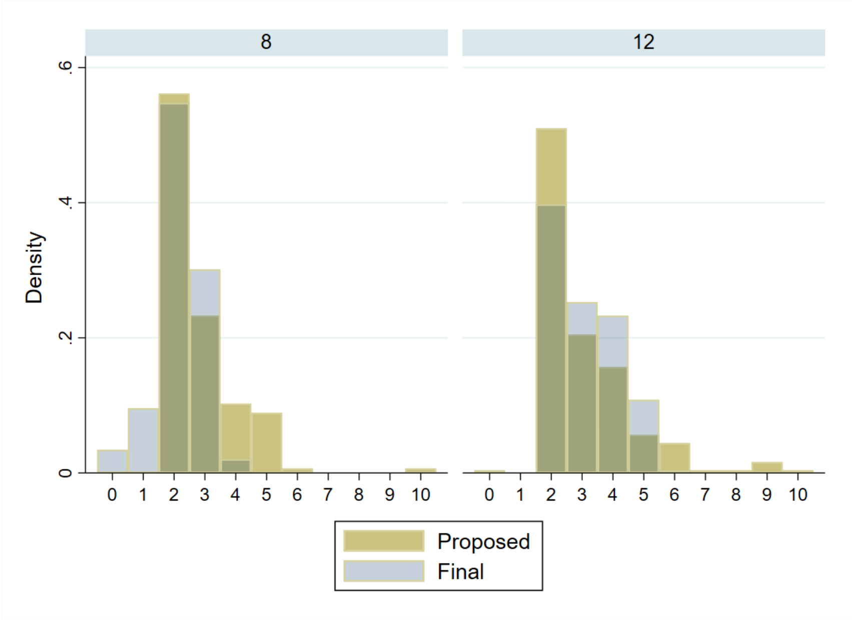

Figure 4.3: Data Sharing by Budget

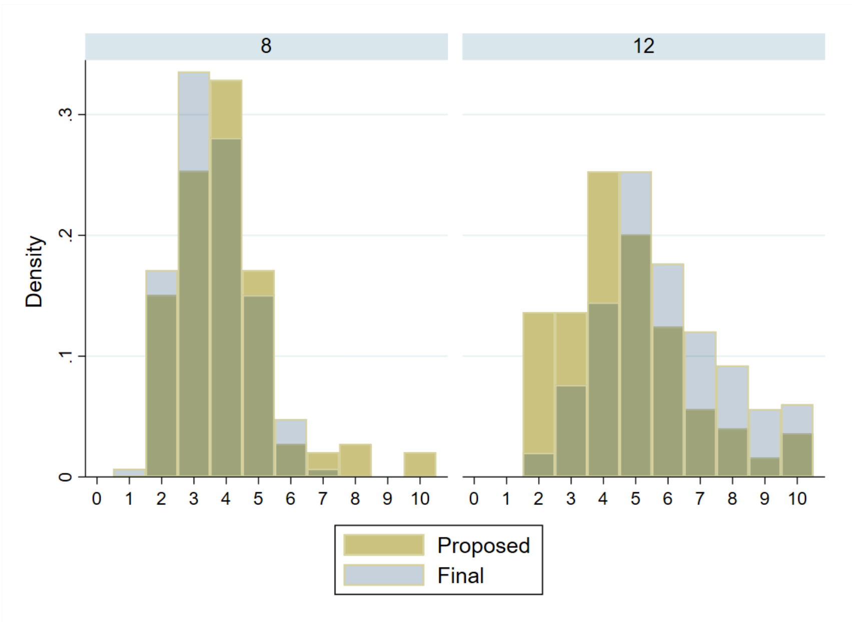

Figure 4.4: Publication by Budget

The competitiveness of the environment has no effect by itself. That being said, Figure 4.3 demonstrates that there is a significant difference in data sharing behavior regarding Researchers with different budgets, even though rational actors should disregard it in every case. Figure 4.4 shows a difference in the number of publications between the two groups which is a fundamental feature of our design. With regards to both data sharing and publication performance, we find a significant difference between successful and unsuccessful Researchers regarding both proposals (data sharing $p=0.0678$, publication $p=0.0003$), and what they end up carrying out later in the round (data sharing $p<0.0001$, publication $p<0.0001$). Unsuccessful (Low Group) Researchers tend to under-deliver compared to their proposals, while successful ones (High Group) tend to not just follow through, but have higher final results than what they initially proposed. It should also be noted that the competitiveness of the setting affects the chances of Researchers to be successful (High Group). Therefore this difference is expected regarding publications, but in the case of rational players, the data sharing behavior should be unrelated.

Accordingly, when looking specifically at the different types of noncompliance, there are 120 cases regarding data sharing, 175 cases regarding publications, and 96 of them involving both. This implies that participants are not behaving strategically: they do not purposefully break with data sharing proposals to be able to maximize publications but fall short on both accounts due to chance. This suggests that even in this artificial setting participants see data sharing to be beneficial in some way, even without any pronounced incentives, and attempt to carry out what they propose.

Our experiment also highlights the importance of defaults that ensure a minimum of data sharing. Since the main focus for the whole design (just as in real life) is on publications regardless of treatment, participants naturally focus on that option to increase their payoffs and are comparatively less likely to increase their data sharing. Even in the "Carrots" treatment, a relatively small but direct incentive for sharing does not have a significant effect on sharing, likely because the benefits received from publications still dominate the benefits from sharing. Despite all this, we find that if the Researchers have more resources available to them, they spend more on data sharing too, not just on publications. This suggests that they have no inherent aversion to share, but do need to have the capability to do so.

4.3.2 Research Institutions

Overall we find that Research Institutions choose to Overlook, Punish, or Report their Researchers in roughly equal proportions in case of non-compliance. Looking more specifically at the budgets of the Researchers, we find a clear difference in the behavior of Research Institutions (Figure 4.5).

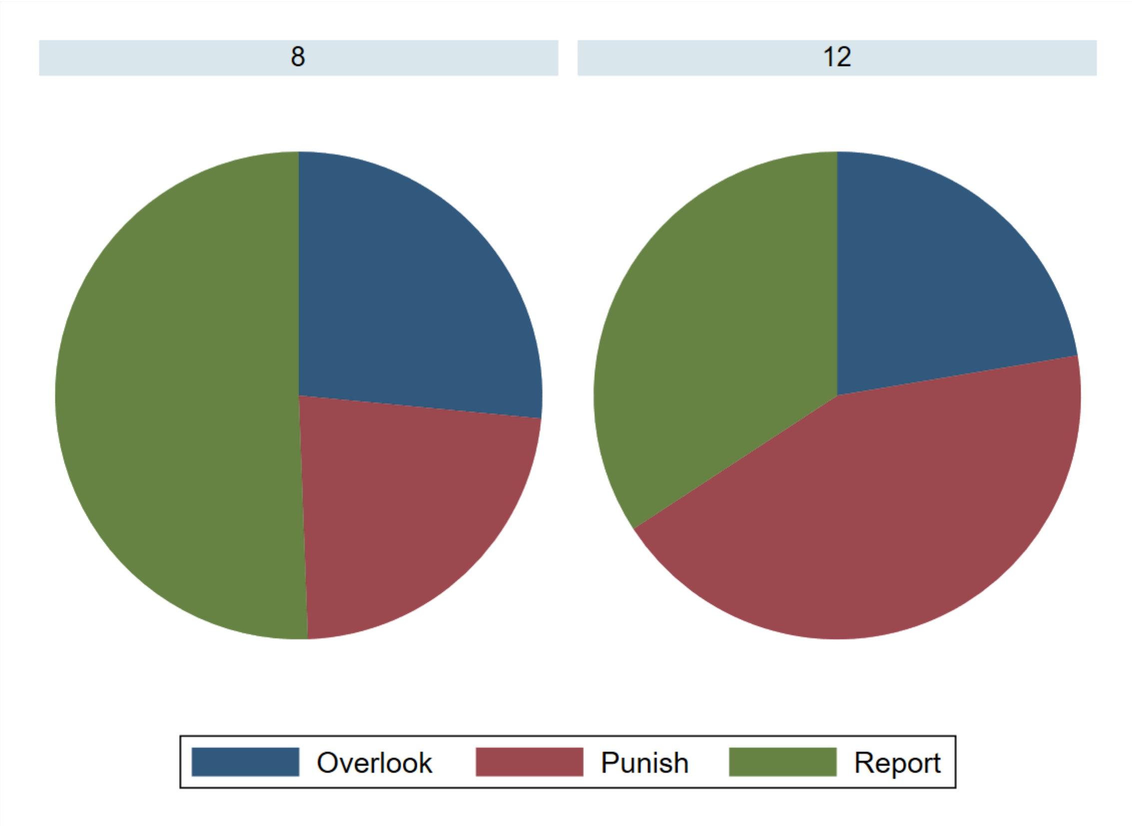

Figure 4.5: Monitoring by Budget

Considering both types of noncompliance jointly, successful (High Group) Researchers are more often Punished and less often Reported compared to their unsuccessful (Low Group) counterparts. This appears to be rational on the surface, indicating Research Institutions maximizing their payoffs. The optimal decision does however also depend on the type of non-compliance in question (publication or data sharing). Figure 4.6 shows the monitoring decision in case of non-compliance with the publication proposal. On the other hand, we find that in roughly 1/3 of the publication non-compliance cases the Research Institution has chosen to Overlook it, which is clearly irrational in any possible situation. In case of publication non-compliance, they are not completely against Reporting the Researcher. Unlike Reporting, selecting the Punish option could be seen as more hostile towards the Researchers, because it reduces their payoff, but it would also be more profitable for Research Institutions if the Researcher has high performance (since by design they are above the Funding Agency's expectation which the Report option would pay out). Accordingly, we find that successful Researchers are more likely to be Punished than unsuccessful ones.

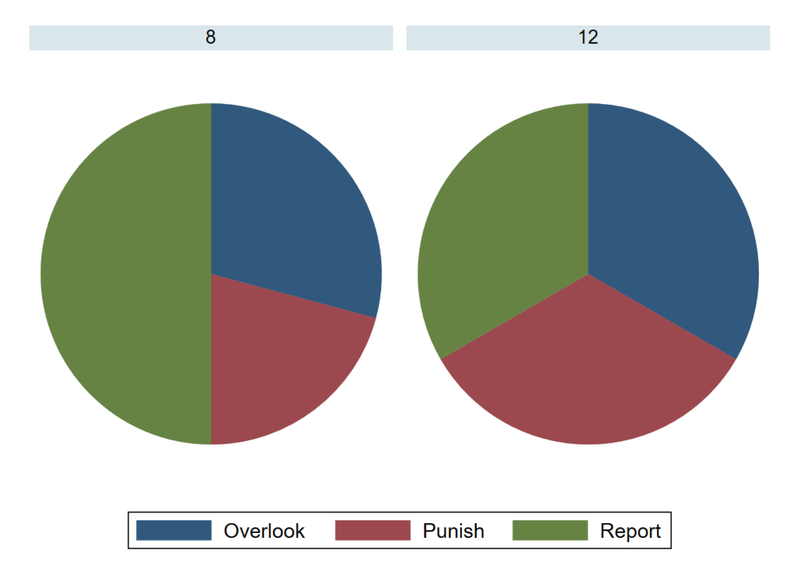

Figure 4.6: Publication Monitoring by Budget

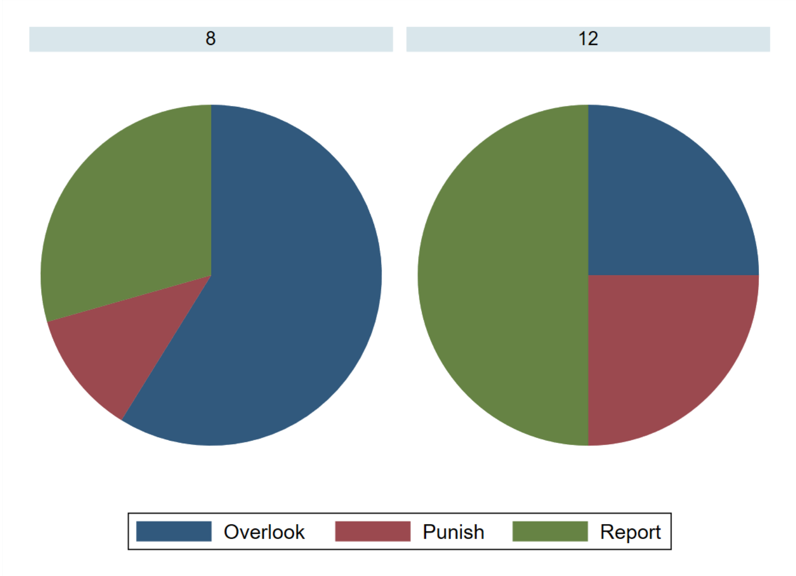

Figure 4.7: Data Sharing Monitoring by Budget

Figure 4.7 shows the monitoring decisions in the cases of non-compliance with the data sharing proposals. In cases of non-compliance of the successful (High Group) Researchers, the Research Institution is most likely to Report them to the Funding Agency. Meanwhile, the Research Institutions are most likely to Overlook the non-compliance of the unsuccessful (Low Group) Researchers.

The Research Institutions' behavior cannot be seen as self-serving, but they are not completely following the Funding Agency's directives either. Importantly, in most cases (69.85%) they carry out some sort of monitoring and do not just Overlook noncompliance.

4.4 Discussion

We find that our participants do not act rationally in any part of the experiment. Researchers do not strategically break their proposals, but share data even without incentives. Similarly, Research Institutions do carry out monitoring even if it is detrimental to their payoffs. We have a set of possible explanations for the behaviors observed in the experiment regarding both roles.

4.4.1 Researcher

By design, the behavior of over-promising and under-delivering is optimal in certain cases. Successful Researchers can rely on their good historical performance and thus are not pushed to propose too high amounts of anything. In contrast, the unsuccessful Researchers could strategically over-promise data sharing, not publications, and under-deliver to try to catch up to the standard expected in each round, and hope the Research Institution does not move against them. We also find that unsuccessful Researchers also tend to over-promise publications, which (unfortunately for them) carries more serious consequences. These Researchers are often unable to comply with their proposals, thus missing out on rounds and falling further behind the standard expected, which leads to a downward spiral.

4.4.2 Research Institution

One explanation for Research Institutions Overlooking data sharing non-compliance is that participants possibly want to avoid conflicts and do not want to be seen as hostile, therefore they are willing to sacrifice a part of their payoff to maintain a good relationship with the other participants. From a different point of view, this could be interpreted as a signal indicating a willingness for cooperation or possible collusion against the interests of the Funding Agency. This behavior can be optimal from a payoff maximization perspective. Depending on the treatment, there is no or a very small chance for the Funding Agency to find out about deviations from proposed data sharing, therefore the risk of not Reporting is quite low. Noncompliance means in most cases that the Researcher has spent more on publications and neglected data sharing, thereby increasing payoffs for both members of the group. The optimal decision of the Research Institution would be to Overlook, but this is not what we find in the experiment. As previously mentioned, we find a difference in how Research Institutions treat successful and unsuccessful Researchers. The successful ones are more likely to be Reported, but unsuccessful ones are predominantly Overlooked. This looks as if Research Institutions act more rationally concerning unsuccessful Researchers, but a more plausible explanation is that social preferences play a role here. The multifaceted behavior of the Research Institutions indicates that they do understand the responsibilities that they have been given by the Funding Agency, but their incentives are not fully aligned with them. Aside from the Funding Agency, they also have to consider the interests of their Researchers, since they have to work together and their incentives are more closely aligned. Naturally, they also have their well-defined self-interests as well, which again pushes them to a different kind of behavior, as described in section 4.2.6.

4.5 Limitations

We consider it to be important to acknowledge that, although we attempted to incorporate as many features of the real-world situation as possible, our experiment is by no means a perfect representation of it. A downside of even this amount of realism is the fact that the experiment is rather complex, and participants had to spend a significant amount of time reading and understanding the instructions. However, we are confident, due to our measures of increasing and testing comprehension, that participants did understand the setting, and that also shows in the results.

It should also be noted that, even though we found no significant differences between treatments, we only tried relatively ”weak” interventions deemed to be realistic. Stronger interventions would likely prove to be effective if they managed to overcome the strong and salient constraints set by the Researchers' budgets.

4.6 Conclusion

We examined the relationship between Researchers, Research Institutions, and Funding Agencies in the context of producing scientific work and sharing research data. Participants were assigned into groups of two, one playing the role of a Researcher and the other the role of a Research Institution, while the behavior of the Funding Agency was automated. We found no meaningful differences regarding behavior between treatments where a small incentive for sharing was provided, or a threat of the Funding Agency of finding noncompliance with data proposals was present. The different levels of competitiveness in the setting also only mattered so far as affecting the success of Researchers, and did not have a direct impact. This is most likely because we only had minor differences between the settings, as well as moderate differences regarding resources between successful and unsuccessful researchers. We propose that if a research environment is more competitive, or the penalty for being unsuccessful is higher, the researchers would be forced to share less.

Our experiment indicates that the real difference is between successful and unsuccessful Researchers, i.e., those with high and low amounts of funding. Data sharing is generally governed by the amount of resources available for it, instead of small-scale interventions increasing punishment or rewards. If their budget allows Researchers to share more data, they do so, even if it does not bring them any direct benefits. They also aim to follow through on the proposals made to the Funding Agency and do not strategically skim on complying with sharing proposals to maximize their payoffs. The minimum required proposal for sharing is a strong focal point for Researchers both in the case of proposals and for actual implementations, which highlights the importance of default options.

In the case of Research Institutions, we find that in most cases they do carry out some sort of monitoring of their Researchers if they do not comply with their proposals. Depending on the circumstances, Research Institutions are more willing to Report the Researcher to the Funding Agency, Punish them, or Overlook their incorrect behavior. We find that our participants in the role of Research Institutions do not maximize their payoffs, nor do they completely follow the directives of the Funding Agency, but also care about the social aspects and cooperate with their Researchers against those interests.

In conclusion, our participants seem to treat data sharing as prosocial behavior even in this abstract setting, and do it for little or no monetary benefit to themselves, even potentially sacrificing part of their payoffs. They also aim to share more if they have the resources to spare, demonstrating that sharing is a salient option, but they are constrained in their ability to do so. Monitoring behavior is also subject to social preferences, and does not completely follow purely selfish payoff-maximizing behavior.

In the context of the real-world application under consideration, our findings suggest that intrinsic motivations and pro-social tendencies significantly contribute to the sharing of research data. This holds especially true in scenarios where resource limitations do not critically impede future productivity. Our research indicates that minor incentives or penalties have a negligible impact on data sharing practices, underscoring the necessity of approaches that neutralize the opportunity costs associated with data sharing. The mechanism by which this equilibrium is achieved appears to be secondary, given that the primary drivers (intrinsic motivation and social preferences) naturally incline researchers towards sharing their data. Implementing default options for data sharing could serve as an auxiliary strategy. However, it is crucial to ensure that such measures are accompanied by adequate resources to carry them out. This is to prevent an undue burden on those researchers who are already most affected by the opportunity costs of data sharing. Expanding on this, future initiatives aimed at enhancing data sharing within the scientific community should focus on creating an environment where the sharing of data is perceived not only as a normative behavior but also as one that is facilitated by institutional support and resources, thus fostering a more collaborative and open scientific landscape.

5. Social Conformity to Bots

Author

Tamas Olah

Abstract

This experiment examined the effects of social conformity on participants facing a unanimous majority of bots providing answers to both objective and subjective questions. We recruited 72 participants from the subject pool of Heidelberg University to take part in a simulated "Quiz Show". They were incentivized to select the correct answers to general knowledge questions, while also being presented with subjective opinion statements concerning economic policy. Using a within-subject design, participants were first asked to indicate their responses without manipulation. Then, after a brief interlude, they had to answer the same questions while seeing the answers of 3 bots similarly to Asch (1951, 1955, 1956). Participants were expressly told that they would be playing with a group of bots. To make the "Quiz Show" setup more salient and to humanize the bots, participants were asked to input a username and select a profile picture generated using the tools by Wang (2019). The responses from the bots were displayed to them with a profile picture and username as well.

We find significant conformity with regard to both objective statements and subjective opinions, both if it is supporting or opposing the subject's own beliefs. We find no significant difference between conformity to opposing or supporting (but more extreme) opinions. We observe a significant difference between the conformity rates of the different genders, with women appearing more likely to conform. We also find evidence that suggests objective and subjective conformity are motivated by different personality traits.

Keywords

Social Conformity, Subjective Conformity, Objective Conformity, Bots

5.1 Introduction

Social conformity has been a widely studied subject in psychology ever since Asch (1951, 1955, 1956) has shown that people are willing to conform to the opinion of a unanimous majority even if it is blatantly and obviously wrong. Since then research on this general topic has splintered into numerous directions. Some stayed closer to the original work (Beran, Drefs, Kaba, Al Baz, & Al Harbi, 2015), others just used computerized agents (Wijenayake, Van Berkel, Kostakos, & Goncalves, 2020), while others have been showing statistics on the opinions of others instead of providing individual opinions (X. Chen et al., 2022; Wijenayake, van Berkel, Kostakos, & Goncalves, 2020). An overarching theme is that all these studies use deception in one way or the other, telling participants that they are seeing the opinions of real humans while in reality these are fabricated. Another angle for research is conformity to non-human agents which makes use of algorithms in a transparent way. Some have used robots (Qin et al., 2022; Salomons, Van Der Linden, Strohkorb Sebo, & Scassellati, 2018) or virtual reality (Kyrlitsias & Michael-Grigoriou, 2018) to closely replicate the original design, but these often led to conflicting results. There is also a disagreement comparing conformity in objective and subjective domains. Additionally, most studies usually examine only one of them, which makes evaluating the connection between them difficult. Different studies use different designs which further hinders comparisons of conformity rates.

The study of social conformity should perhaps be more important than ever in the current social and political climate. In this day and age, social media has an unprecedented impact on our lives, famously influencing elections, spreading misinformation and conspiracy theories, or even fostering extremism. It has been well established that people are likely to conform in an online setting (Sukumaran, Vezich, McHugh, & Nass, 2011) to comments and sentiments left by others (Colliander, 2019), and this is likely affected by perceived social presence (Wijenayake, van Berkel, Kostakos, & Goncalves, 2022). One important element is the presence of echo chambers where opinions leaning in the same direction reinforce each other and can all too often lead to polarization and extremist beliefs (Quattrociocchi, Scala, & Sunstein, 2016). It is an ongoing debate if and how people could be broken out of this vicious circle. Another important problem is the presence of bots that can be potentially used to influence public opinion. It is believed that 5% to 20% of Twitter users (Duffy & Fung, 2022; Varanasi, 2022) and up to 36% of Facebook users (Nicas, 2019) are not real people but bots that try to steer public opinion. Despite these high numbers and people generally being aware of the problem, their social influence still persists. This problem is likely to escalate in the future with the advent and rapid spread of generative AI that is becoming indistinguishable from actual people.

In this study, we aim to investigate social conformity in both objective and subjective domains, using a setup similar to Asch's original study, but with the crucial distinction of transparently using bots. Unlike the original study, which deceptively used real people as confederates, we have shown three bots on a computer which were represented by AI-generated pictures, and nicknames. Instead of the classic line recognition task, our objective setting involves a general knowledge test, while our subjective setting investigates participants' opinions on economic policy. By using transparent methods and bots, we hope to shed light on the complex phenomenon of social conformity in a contemporary context.

5.2 Methodology

5.2.1 Participants

The English-language experiment was conducted in person at the lab of Heidelberg University in the summer of 2022. 72 participants were recruited from the university's subject pool, and to avoid demand effects as much as possible, they were only told that they would take part in a study involving a ”Quiz Show”. Among the participants 47.22% were female, and the average age was 22.99 (SD = 3.446). The overwhelming majority of participants (84.72%) leaned to the political left, with a small portion (8.33%) being neutral, and only a few (6.94%) leaning to the right.

5.2.2 Study Design

The main purpose of our study was to see if participants conform to the opinion of a unanimous majority of bots, even though they are consciously aware that these are bots and not real people. Secondly, we wanted to see if there is a significant difference between conformity to a majority where bots support either a more extreme version of the subject's own political beliefs, or their opposite. Thirdly, we wanted to know whether participants react differently concerning objective and subjective topics.

For this reason, we created a simulated ”Quiz Show” using oTree (D. L. Chen et al., 2016) and a two-treatment design: one where the bots ”support” and one where the bots ”oppose” the participant's own political beliefs. Within these treatments, we used a within-subject design to elicit conformity. The procedure has the following stages:

1. Welcome and introduction to the experiment
2. Risk attitude
3. Quiz questions without manipulation (Control)
4. Personality Questionnaire (Big Five)
5. Self-reported proficiencies in the topics included among the Quiz questions
6. Instructions clearly stating the Quiz will be played with bots
7. Quiz questions as in Control but in different order and manipulation (Treatment)
8. Participants' opinions on the bots
9. Trust Game involving the participants and one of the bots
10. Demographics
11. Results with feedback showing participants their earnings

First, we started with an overview of the experiment framing it as a ”Quiz Show” to participants to avoid the demand effect as much as possible. Then we elicited participants' risk preferences (Eckel & Grossman, 2008) to see if it mediates conformity or their beliefs about the bots.

In both the Control and Treatment parts of the experiments, participants were shown a set of questions and a set of possible answers. These questions were displayed one by one, and participants were asked to indicate their answers by simply clicking one of five buttons. To make the ”Quiz Show” framing more salient, they were given 20 seconds to do so in the Control, and 10 seconds in the Treatment part of the experiment. Subjects were not given feedback between the Control and Treatment on the correctness of their answers.

For the objective part, we used 23 general knowledge questions. Participants' payoffs chiefly depended on giving accurate answers to the objective questions in the Treatment part, and for this reason, the Control part was presented to them as a practice round. This was to further develop the ”Quiz Show” setup, thus reducing the demand effect. The bots' answers were fixed, meaning they always gave the same answer to a question regardless of the participant's choice. All the bots gave the same answers to 20 of the questions, and in the remaining three cases, they conflicted in order to distract from the manipulation.

For the subjective statements, we used six of the 8values `https://8values.github.io/` survey economic policy questions. The bots' responses were calculated dynamically for each participant depending on the choices made in the Control part. The subjective answers were marked on a 5-point Likert scale, ranging from ”Strongly Agree” to ”Strongly Disagree”. The bots were set to push by 2 steps on this scale to either ”support” or to ”oppose” the participant's initial opinions depending on the treatment. We also took the participant's general political leaning into account to determine the direction in each case.

If the participant selected ”Strongly Agree” in the Control, then in the Treatment with bots opposing the participants' beliefs the bots would select ”Neither agree nor disagree”. Likewise, if the participant selected ”Agree”, then the bots would pick ”Disagree”. In case the participant picked ”Neither agree nor disagree”, the response was either ”Strongly Agree” or ”Strongly Disagree” depending on overall political leaning. Figure 5.1 demonstrates the bots' responses for each possible option in case the participant was on the side supporting the statement.

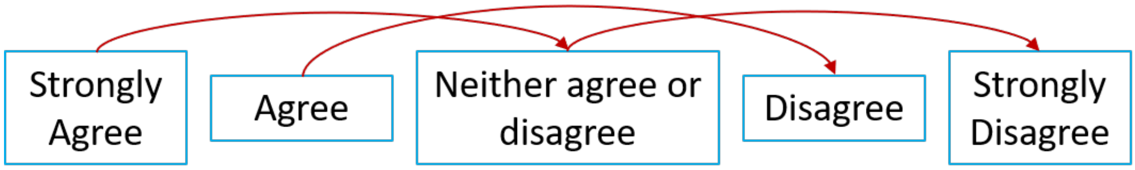

Figure 5.1: Bots' oppose responses

The version where bots supported the participant's beliefs worked similarly. If in line with the participants' overall beliefs, "Agree" and "Disagree" was moved to "Strongly Agree" or "Strongly Disagree", if not in line, "Disagree" or "Agree" was displayed, respectively. In the same way, "Neither agree nor disagree" became "Strongly Agree" or "Strongly Disagree". All three bots always gave the same responses to the statements. Figure 5.2 shows the bots' responses in case the participant supported the overall political side agreeing with the statement.

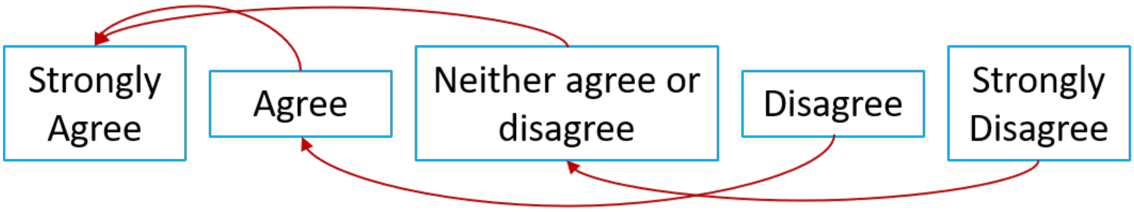

Figure 5.2: Bot support responses

In the treatment condition, participants had to give their answers after that of three bots. To humanize the bots, they were represented by AI-generated faces (Wang, 2019) and a nickname. Before taking part in the "Quiz Show" participants were also asked to select a profile picture and type in a nickname to represent themselves. This was done to reinforce the social aspect of the situation, even while consciously being aware that the others were not real people. It was necessary that participants see the others as their peers because without a social aspect, there can be no social conformity in any given situation. So in our experiment, despite clearly telling participants that they would be playing with bots and while avoiding any deception, we aimed to make the bots feel as "human" as possible. Additionally, to further humanize the bots, when the bots were giving their responses, there was a short wait period between each answer to give participants the impression that they were "thinking". The purpose behind all of this was to approximate how bots used to manipulate are represented online on various platforms.

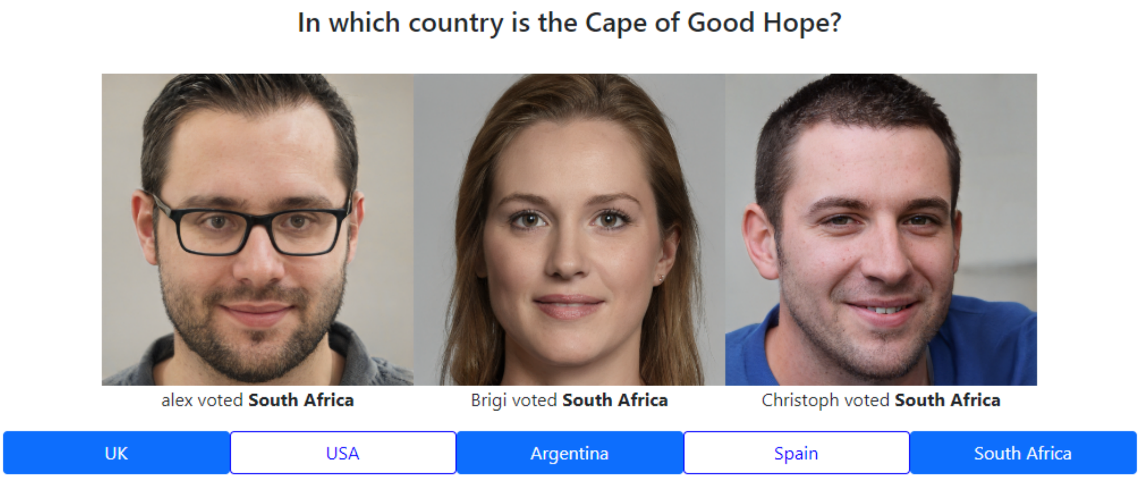

Figure 5.3: Objective Questions in the Treatment

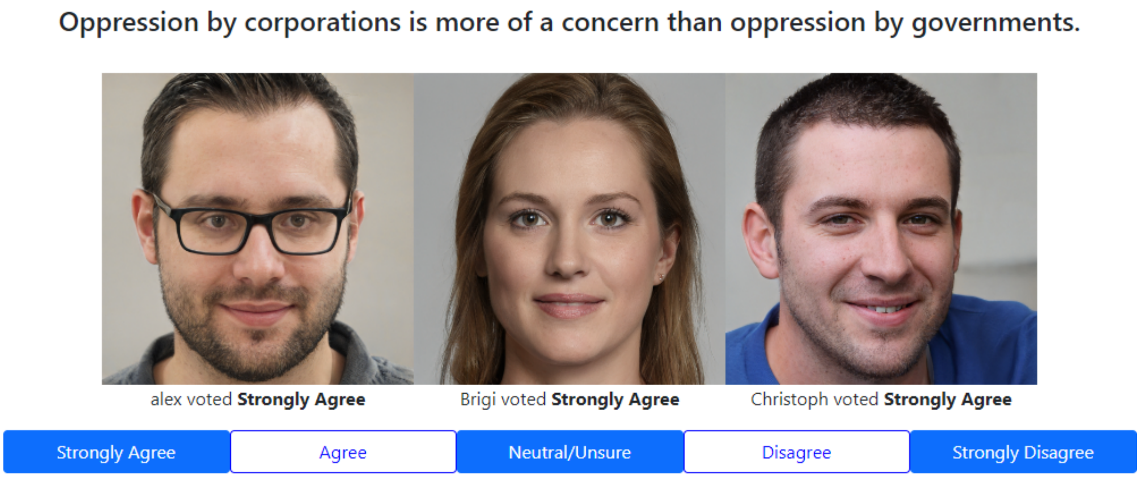

Figure 5.4: Subjective Questions in the Treatment

Figure 5.3 and Figure 5.4 are two examples of what participants have seen in the Treatment part of the experiment. The same pictures and nicknames were shown to all participants and were not changed during the course of the experiment. Participants were given a timer above the question indicating how much time they had left for the given question, counting back from the allotted 10 seconds. They could intuitively provide their answer by simply clicking on the desired button.

After the "Quiz Show", we wanted to determine if participants think about the bots more like people or machines. To avoid biasing them in either direction, we first asked them to write something about the "others" in their group. This was mainly to see if they mention those being machines which should have been their most salient trait. To further investigate this question, we also made each participant play a Trust Game (Berg, Dickhaut, & McCabe, 1995) with one of the bots to see if they just treat this task as a risky choice, or behave like the bot is a social agent.

5.2.3 Calculating Conformity Rates

Both in the case of objective questions and subjective statements conformity rates were calculated by checking how much a participant conformed out of the maximum conformity possible for them. Conformity in objective and subjective cases had to be quantified in different ways, as the possible answers are fundamentally different from a psychological point of view.

In the objective case, general knowledge questions have clear and correct answers, which can be verified through evidence, logic, or prior knowledge. For example, "In which country is the Cape of Good Hope?" has a concrete answer, which is "South Africa". In such cases, the possible answers are not connected to each other, and we can rely on discrete choices to detect conformity. Thus, conformity choices refer to selecting one of the options presented to participants that was supported by the bots, unless they had already selected this answer in the Control condition.

As for objective questions, we compared the participants' answers from the Control part of the experiment to that from the Treatment to see how many times they changed to conform with the answers of the bots. Since the bots' answers were fixed, we were able to calculate how many times it was possible for participants to modify their answers to match that of the bots. Then, we filtered out the cases where the participant gave the same answer in the Control part as the bots in the Treatment part, as in those cases no conformity was possible. Conversely, we have also tracked possible anti-conformity where participants could modify their answers explicitly to avoid not coinciding with that of the bots. Thus we calculated the objective conformity rate (OC) by dividing the number of conformity choices (n_{oc}) by the number of all possible conformity choices (max_{oc}), then from this, we subtracted the number of anti-conformity choices (n_{oac}) divided by the number of possible anti-conformity choices (max_{oac}).

$$OC = \frac{n_{oc}}{max_{oc}} - \frac{n_{oac}}{max_{oac}}$$

However, when it comes to subjective opinions, the answers are not as clear-cut as the objective ones. Here, none of the possible answers can be judged as being objectively right or wrong and thus should be evaluated on a spectrum. For example, the statement "Oppression by corporations is more of a concern than oppression by governments" does not have a single, definitive, and correct answer. Some people may "Strongly Agree" with it or may "Strongly Disagree" with it, while others may even be neutral. As such, the possible answers form a continuous spectrum, with a range of possibilities that are not easily reducible to discrete conformity choices. Therefore conformity in this case refers to movement on the scale in the direction of the opinions stated by the bots.

For this reason, regarding subjective statements, we have calculated a political opinion score based on the first part of the experiment. Then we calculated the bots' responses either supporting or opposing the subjects' political side as previously described. This way we could track how much a participant moved their opinion in relation to the bots' stated opinions in the second part of the experiment. Just as in the previous case, we have also considered the possibility of anti-conformity, where participants could be averse to the bots, and deliberately move against their opinions. As such we calculated the subjective conformity rate (SC) by seeing how much their political score changed in the Treatment ($polscore_{treatment}$) compared to the Control ($polscore_{control}$) part of the experiment and divided it by how much change was possible - the difference between the subjects' score in the Control ($polscore_{control}$) compared to the bots' score ($polscore_{control}$). The direction of the subtractions depended on whether participants were in the support or oppose treatments, as well as their political score.

$$SC = \left| \frac{|polscore_{treatment}| - |polscore_{control}|}{|polscore_{bot}| - |polscore_{control}|} \right|$$

Thus, we considered conformity not for each decision separately, but based on the subjects' overall behavior throughout the experiment. While objective and subjective conformity rates might not be directly comparable, the calculated values should at the very least indicate in which case conformity is stronger.

5.3 Hypotheses

In this experiment, we expected participants to conform to the bots, even when it is abundantly clear that they are not real people, and that the participants have no real reason to conform. Due to the "humanization" of the bots, our subjects should have experienced a certain amount of social pressure, where they would be drawn towards agreeing with their "peers".

Due to their conceptual differences, objective and subjective conformity are suspected to be motivated by different factors. We propose that objective conformity is likely the stronger of the two, due to an informational effect. Especially in the cases of high uncertainty about the correct answer, participants have no real incentive not to select the option supported by the bots. For this reason, we expect objective conformity to be closely related to our participants' self-rated proficiency.

Conversely, we hypothesize subjective conformity to be the weaker of the two, due to being solely motivated by social factors. In this case, participants have no real incentive to conform to the bots. Because of this, we expect conformity to be motivated by various personality traits. We also propose that bots supporting the participants' personal opinion are likely to elicit a larger amount of conformity compared to the opposing condition. Participants could be more likely to accept a more extreme view of their opinion rather than a completely opposing one.

5.4 Results

5.4.1 Objective conformity

As mentioned above, we measured objective conformity using 23 general knowledge questions, first presented to participants without manipulation, then – after a short interlude – while seeing the answers of three bots. Previous research established that objective conformity could be broken down to two separate factors, namely an informational and a normative element (Toelch & Dolan, 2015). It can also be affected by participants trying to maintain a positive self-concept and move towards socially favourable behaviors (Cialdini & Goldstein, 2004; Wijenayake, van Berkel, et al., 2020). Participants have an incentive to conform if they are not confident about their answers because they could think the bots are more knowledgeable about the subject, even more so as there are three of them in agreement, which could signal confidence or correctness of their answer. The normative element refers to the fact that humans as inherently social beings participants could be hesitant to go against the group opinion, and would change their answers to fit in. Participants were clearly told that they would be playing with bots that have decision-making capabilities comparable to an "average person". This was intentionally left vague with the aim to both "humanize" the bots and to communicate that they are not infallible and should not be unquestionably followed. Thus, for a rational person, there should not be any normative effect and only a very limited informational effect in cases where they consider themselves less knowledgeable than average. Maintaining a positive self-concept can result in a motivation for both conformity and anti-conformity. On the one hand, participants would want to be right and achieve high payoffs, but would also probably be averse to conforming to bots and admit that those are smarter than themselves.

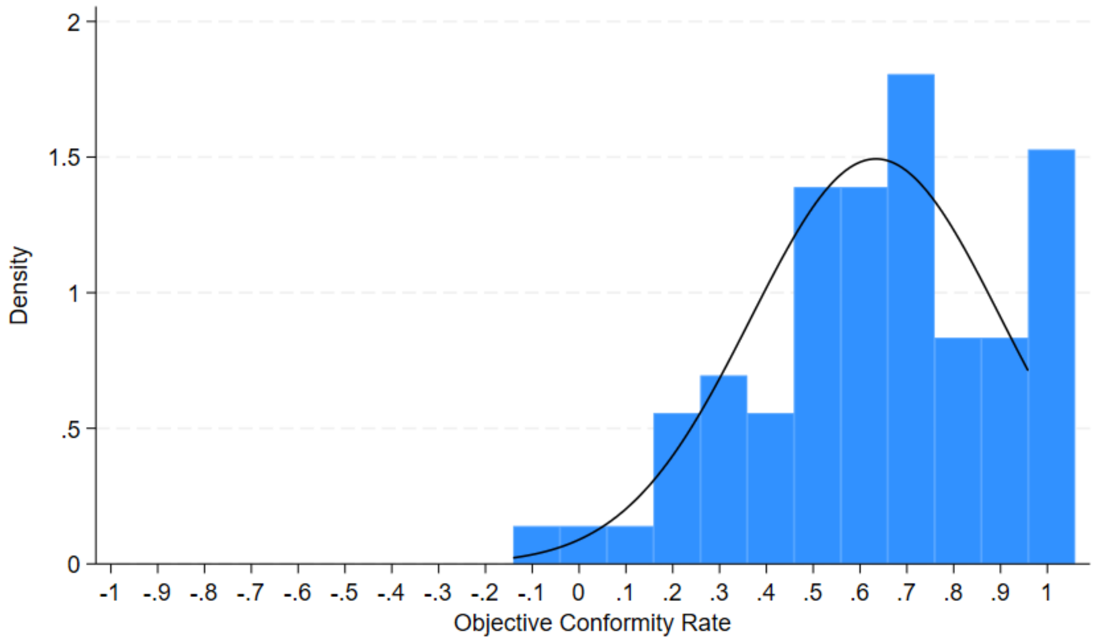

Figure 5.5: Objective Conformity Rate

Despite these points, as Figure 5.5 shows, our participants exhibit very high levels of conformity. As such we find overwhelming evidence for the existence of objective conformity ($p<0.001$). On average, participants have exhibited a conformity rate of 63.4% (SD=0.267) which is considerably higher than most other studies have found (Bond, 2005). We also find evidence for a gender effect, where female participants conform significantly more than male participants ($p=0.0136$). As expected, the fewer answers a participant got correct in the Control part of the experiment, the more likely they were to conform in the Treatment part ($p=0.003$) demonstrating the importance of the informational element behind conformity. We find no difference between objective conformity in case the bots either support or oppose the subjects' political opinions.

To confirm if uncertainty about the correct answer indeed motivates conformity, we have also asked participants to report their familiarity with the main topics covered in the general knowledge questions, as well as some that were not included in the quiz. These were elicited using a 100-point scale where subjects had to move a slider according to how knowledgeable they would report themselves to be.

	Objective Conformity Rate
History	-0.004**
	(0.002)
Linguistics	0.002
	(0.001)
Geography	-0.003*
	(0.001)
Politics	0.003*
	(0.002)
Constant	0.696**
	(0.076)
Observations	72
Note	*p<0.05; **p<0.01

Table 5.1: Self-reported familiarity with topics

Most of our questions referred to geographic or historical trivia with no questions regarding linguistics or politics. Table 5.1 shows how self-reported familiarity with these topics affects objective conformity. Just as having answered more questions correctly, being more familiar with relevant topics included in the quiz show leads to lower levels of conformity. Unexpectedly, being more familiar with topics irrelevant to the quiz appears to correlate with higher conformity.

5.4.2 Subjective conformity

For our subjective statements, six of the 8values survey's (`https://8values.github.io/`) economic policy questions were utilized, first without manipulation, and then with the unanimous opinions of three bots. In contrast with objective conformity, subjective conformity only has a normative element without an informational one, and it might also be affected by participants wanting to maintain a positive self-concept. As there is no "right answer", participants have nothing to learn from the bots. From the perspective of normatively driven conformity, subjects would like to fit in with their group. But just as before, assuming participants are rational, they would have no incentives to change their opinions to fit in, since bots are not social agents in reality. Additionally, maintaining a positive self-concept would most likely push against conformity with a bot. For these reasons, while in the case of objective questions, the three factors should reinforce each other to induce conformity, in the case of subjective topics one factor is likely to push conformity while another is acting against it.

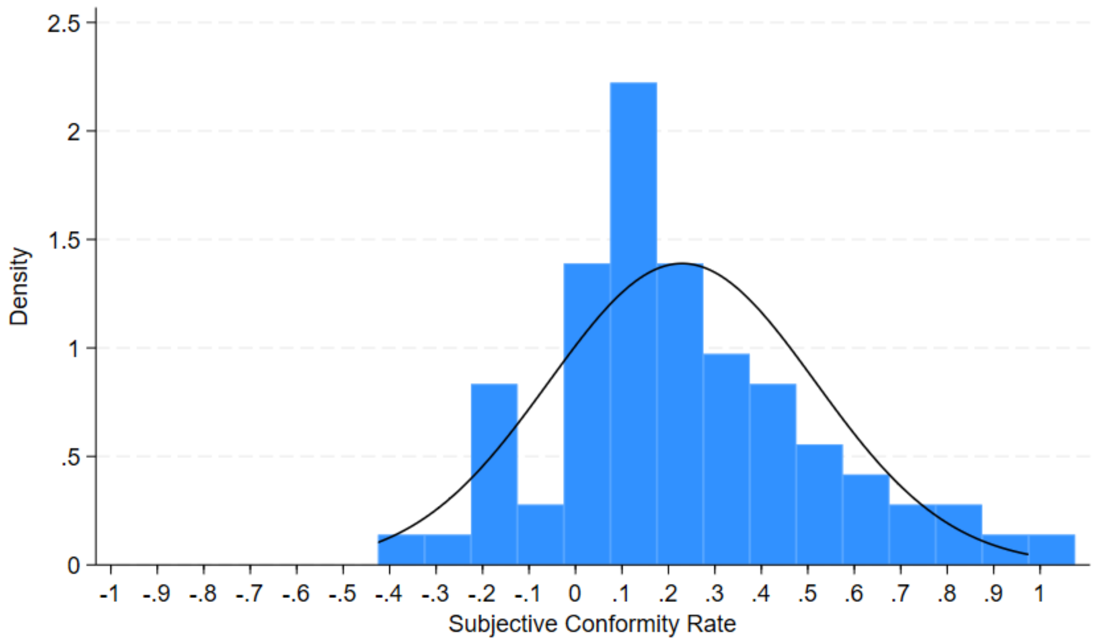

Figure 5.6: Subjective Conformity Rate

Figure 5.6 illustrates that participants' behavior deviates from rationality, being significantly influenced by bot responses. Our analysis reveals substantial evidence of conformity within the subjective domain, with a statistically significant finding ($p < 0.001$). On average, a conformity rate of 22.9% (SD=0.287) was observed among participants. Similarly to objective conformity, our findings also demonstrate a gender-based difference in conformity rates, with female participants exhibiting a significantly higher tendency to conform compared to their male counterparts ($p = 0.0056$). Intriguingly, participants who answered fewer objective questions correctly in the control segment of our study were more inclined to conform when expressing subjective opinions (p=0.006), suggesting a potential lack of confidence in their own expertise. However, no significant correlation was found between participants' self-assessed proficiency and conformity behavior. Furthermore, our results indicate a strong connection between objective and subjective conformity (p=0.007), suggesting that the phenomenon of conformity transcends the distinction between these domains. Notably, we observed no statistical difference in conformity levels when participants were faced with supporting versus opposing majorities. This collective evidence suggests that participants, particularly those uncertain of their own abilities, may have attributed greater validity to the bots' expertise. Consequently, this indicates that conformity observed in the objective domain may extend into the subjective domain, highlighting a nuanced interaction between self-perception of skill and the propensity to conform.

5.4.3 Factors driving conformity

Aside from the self-rated proficiency, participants were asked to fill out a short Big Five personality questionnaire (Lang, John, Lüdtke, Schupp, & Wagner, 2011) between the Control and Treatment parts of the experiment. Previous research has tried to relate the Big Five traits to conformity decisions (Wijenayake, van Berkel, et al., 2020), but did not examine whether the personality traits driving objective and subjective conformity might differ.

	Objective Conformity Rate	Subjective Conformity Rate
Extraversion	0.019 (0.021)	0.003 (0.026)
Agreeableness	0.023 (0.024)	0.006 (0.029)
Conscientiousness	0.078* (0.035)	0.019 (0.033)
Neuroticism	0.047 (0.024)	0.044 (0.027)
Openness	0.027 (0.034)	0.078* (0.031)
Politics	0.020 (0.014)	-0.020 (0.011)
Constant	-0.332 (0.337)	-0.436 (0.307)
Observations	72	72
Notes	*p<0.05; **p<0.01	

Table 5.2: Effect of Big Five traits on Conformity

Table 5.2 shows the results of regressing the different categories of conformity on the Big Five traits while considering the participants' political beliefs. Here we find that objective conformity is driven mainly by the trait Conscientiousness and possibly Neuroticism although that is not statistically significant at the 5% level. Meanwhile, in the case of subjective conformity, we find the trait Openness to be the most significant trait (p=0.015). Here again, Neuroticism might play a role, but it is not statistically significant at the 10% level.

The higher a participant ranks in Conscientiousness, the more likely they are to conform regarding the general knowledge questions. A possible explanation for this is that highly Conscientious participants have a higher psychological need to answer questions correctly, or reversely are more averse to being wrong. Thus, in case of doubt, a possible answer supported by the bots would appear more attractive. These participants likely also take the ”Quiz Show” more seriously and consider it important to perform well and get higher payoffs, or simply wish to avoid being wrong.

On the side of subjective conformity, the Openness trait is the main driving factor. This points to participants who are more open to new ideas and are more likely to consider the ideas proposed by the bots. It hints that participants treat the bots as social actors, and consider their opinions plausible.

We have also found that the strengths of a subject's political beliefs have a significant negative effect on subjective conformity. The further the participants lean to the political left, the less likely they are to conform to the opinion of the bots. This point should, however, be considered with some reservation, as our sample is heavily skewed towards the political left.

We also elicited the participants' risk attitude (Eckel & Grossman, 2008) and found that the more risk averse they are, the more likely they are to conform in the subjective case ($p=0.051$).

5.4.4 Opinion on bots

As previously mentioned, our goal was to know if participants treat the bots as just machines or more as social beings. How participants perceived the bots is an important consideration, as establishing the presence of a social aspect in the situation is integral to proving the existence of social conformity. Additionally, from a methodological point of view, it is crucial to know whether subjects actually realize and remember that they are playing with bots. Even if we clearly disclosed that participants would be playing with bots, using no deception whatsoever in the experiment, participants might be inattentive and forget this part of the instructions.

To gain a deeper understanding of what participants thought about the bots, we asked an open question at the end of the experiment inquiring what they thought about the ”others” they had been playing with. At this point, we did not point out again that they were bots because our interest was whether participants remembered that they were not playing with real people. Here the vast majority of participants (90.28%) made no direct mention of their partners being bots. Some outright questioned if they were in fact bots, or talked about them as if they were people, writing things along the lines of ”everybody was quite cautious about what other people wrote - Alex had his own opinion”, or ”The woman was very considerate and is a smart, intelligent person who has a lot of friends. Both guys are smart people, maybe a bit nerdy. Especially Alex knows much, the other guy knows much in his interest fields.”. Curiously some participants seemed to be very immersed in the setup commenting things like ”They are very capitalistic and believe in a neoliberal agenda. I think the past has shown that a totally free market is not always the best solution." or "The hundred year war was not 100 years my dudes". The responses underscore the observation that even when participants were explicitly informed that the "others" were bots, this distinction became less apparent following minimal human-like interaction within an engaging context. This finding bears significant real-world implications, particularly in scenarios where bots are deployed with the intent to influence or manipulate human behavior. Typically, such bots are not explicitly identified as non-human agents. Our results suggest that, even with clear labeling, individuals may remain susceptible to their manipulation. This vulnerability highlights the effectiveness of even basic humanization tactics in obscuring the artificial nature of these entities, raising important concerns about the ease with which digital agents can influence human decision-making and perceptions.

We also asked participants to play a Trust Game (Berg et al., 1995) with one of the bots (Alex) at the end of the experiment. Here we found high levels of trust shown to the bot: Almost 78% of participants offered five tokens or above, and almost 32% offered the maximal amount of 10 tokens. We find no significant differences regarding trust between the treatments, or between genders. There is also no significant correlation between the subject's risk attitude and their choice in the trust game, indicating that they did not consider that game a simply risky choice, but potentially thought about the bots as social actors.

There are a number of plausible explanations for this behavior. Firstly, participants may not have read the instructions carefully and missed out on the part stating that they would be participating in the "Quiz Show" with bots. We consider this relatively unlikely as the instructions for the experiment were relatively short, putting the "bots" in bold, and referring to it multiple times. Secondly, despite reading the instructions and understanding the nature of the bots at the time, during the experiment, this could have been forgotten by the participants. Since the task requires a significant amount of mental effort and the bots are portrayed with a profile picture and a nickname (just like the participants), participants likely felt some connection to them. We consider this the more likely explanation, which is likely the same in real-world settings such as Facebook or X. Thirdly, it is also possible that participants were consciously aware of the artificial nature of the bots, but also treat them as social agents. This opinion also has some parallels in the real world as with ChatGPT or other AI systems, and highlights the power of such technologies. These considerations are all in line with the idea of having to humanize agents to motivate conformity.

5.5 Limitations

The present study aimed to investigate the effects of social conformity on individuals when faced with a unanimous majority of bots. The findings add to the existing literature on social conformity and shed light on the social influence of bots, but unfortunately also involve some necessary limitations.

This experiment admittedly involves a student sample that is by no means representative of the general population. We would argue that our demographic group should be more knowledgeable and suspicious about the subject than the average person, thus if anything our experiment would underestimate the effects of conformity. This should especially be true in the case of the subjective statements since our participant pool is chiefly comprised of economics students whose beliefs regarding economic policy could be expected to be rather strong.

The present study utilized a student sample with a very limited size, which makes the generalizability of our results difficult to determine. Future research should focus on participants with more diverse backgrounds and political opinions to establish what effects these might have on conformity.

5.6 Conclusion

Our findings suggest that the influence of social norms and the desire to fit in with a group can override rational decision-making, even when participants know that the majority is composed of artificial entities (bots). This has implications for understanding how people form opinions and make choices, especially in online environments where social influence is often at play.

The results of this study reveal that participants exhibited significant levels of conformity when faced with a unanimous majority of bots. This was evident in both the objective and subjective domains, indicating that individuals are willing to conform to the opinions of artificial agents, even if they do not necessarily agree with them. Interestingly, the study found no significant difference between conformity to opposing or supporting (but more extreme) opinions, suggesting that individuals may be equally likely to conform to opinions regardless of whether they align with their own beliefs if these are displayed to be supported by a sufficient majority.

Moreover, the study identified a significant difference between the conformity rates of men and women, indicating that gender may play a role in social conformity. Further research is needed to investigate the reasons behind this difference, as well as to explore the potential factors that influence social conformity in general.

The study uncovered evidence indicating that the propensities for objective and subjective conformity are likely influenced by distinct personality traits. This distinction suggests that certain personality characteristics may predispose individuals to conform to objective information, whereas a different set of traits may be linked to conformity in response to subjective assertions. The identification of these specific personality traits and their correlation with modes of social conformity necessitates further investigation. Such research is crucial for a deeper understanding of the underlying psychological mechanisms driving conformity, and it may illuminate the complex interplay between individual personality profiles and social influence dynamics.

The results also suggest that the type of question being asked – be it objective or subjective – can affect the extent to which people conform to the majority. Objective questions, which have a clear right or wrong answer, may be more susceptible to social conformity because, besides a normative component, bots can also exert a perceived informational effect. In case participants feel uncertain about their own knowledge, they conform to the bots, wanting to be right. Subjective statements, on the other hand, may be more resistant to social pressure because there is only a normative influence the bots can produce. Since there is no ”right answer”, and in our experiment, participants have no financial incentive to change their opinion, they have nothing to gain from ”listening” to the bots. Also, individuals are often attached to their personal beliefs and opinions about a subjective topic, especially if it is in their field of knowledge.

The study also highlights the role of personality traits in shaping conformity decisions. Specifically, individuals who score high on measures of conscientiousness and potentially neuroticism in the objective case and openness in the subjective one may be more likely to conform to the majority.

Additionally, the findings suggest that participants' confidence in their answers plays a crucial role in determining whether they conform to the majority or not. This effect is observed not only in objective questions but also (partially) in subjective statements, reinforcing that confidence in one's own opinions can be a powerful factor in shaping decision-making.

Finally, the study provides evidence that simple humanization cues, such as profile pictures and nicknames, can be sufficient to create a sense of social presence and facilitate conformity to non-human agents. This has implications for designing online environments and social media platforms, where bots are becoming more and more prevalent. By understanding how humanization cues affect social influence, it may be possible to design systems that promote more independent thinking and reduce the potential for herd behavior.

6. Conclusions

This research project was designed to elicit how individuals perceive and engage with emerging issues, exploring the effects of these perceptions on their behaviors. The dissertation is comprised of four papers, each contributing unique insights intended to aid decision-makers in navigating the complexities of a rapidly evolving societal and technological landscape. The primary aim was to gain a deeper understanding through a variety of methods, such as the social norm research framework, extending its application to the perceived motivations behind actors, and emergent research areas such as digital privacy and the dynamics of personal data management. This investigation was further built upon by conceptualizing the scientific ecosystem as a tripartite principal-agent model involving researchers, academic institutions, and funding bodies. Additionally, the phenomenon of social conformity in interactions with automated entities on online platforms was scrutinized, a pertinent inquiry given the proliferation of generative AI technologies. Methodologically, it underscores the feasibility of studying social conformity within the ethical boundaries set by the no-deception principle inherent in experimental economics.

The contributions of this dissertation are encapsulated as follows:

1. Investigation of social norms among researchers concerning Open Science initiatives, quantitatively assessed to inform policy and practice.
2. Cross-national evaluation of societal norms regarding the handling and perception of personal data, offering a comparative insight into privacy concerns.
3. Development of a theoretical model depicting scientific inquiry as a three-faceted principal-agent dilemma, aimed at examining the efficacy of varied policy interventions.
4. Introduction of a pioneering methodology for investigating social conformity to artificial entities, reflecting the evolving nature of computerized interactions.

From a pragmatic standpoint, the results offer actionable intelligence for policymakers and stakeholders. Recommendations include crafting policies and systems that effectively address challenges related to personal data governance, Open Science adoption, and the mitigation of manipulative practices in digital domains.

For research funding organizations, this dissertation outlines several strategic recommendations derived from the findings. It emphasizes the intrinsic value researchers place on Open Science as a cornerstone of ethical research practice, highlighting their readiness to support these initiatives, albeit with a need for clear directives and adequate resources. It is also found that researchers predominantly see the sharing of research data as part of good scientific practice, a fact that can be used in support of these policies. However, the majority also thinks that mandatory sharing impedes their work, drawing attention to the fact that policymakers should not simply set requirements, but also make sure the necessary tools and resources are available to achieve them.

Data subjects also demonstrate a set of complex attitudes towards data. Notably, while there is a general acceptance of personal data utilization for scholarly purposes, the commercial or governmental use of such data is met with skepticism. In addition to the informational content of the data, the original purpose for its generation also makes a difference: it is seen as relatively acceptable to share data that was generated for research purposes outside of the scope of the original study, even without express consent from the subjects. Meanwhile, if essentially the same information was collected for a different purpose, participants view the entire situation in a different light. All these show that people are generally quite favorable towards researchers, and think they wish to benefit society with the use of their data. Policymakers could use this fact to implement a broader form of consent for the use of personal data in the domain of research, thus fostering sharing.

Taking a closer look at the scientific landscape, we have modeled this system as a three-sided principal-agent problem between Researchers, Research Institutions, and Funding Agencies. Aimed to investigate how different potential interventions to incentivize data sharing may play out in the scientific ecosystem. Our findings here further reinforce those from the social norm vignettes. Researchers here are willing to put effort into data sharing, even if it has little to no personal benefit for them, but they do need resources to implement it. This experiment highlights that it is important for policymakers to set clear requirements, but they also have to make sure those are actually achievable. Meanwhile, research institutions are willing to monitor and for the most part enforce the implementation of open data policies, even at a personal cost to themselves. At the same time, it also appears that smaller-scale "realistic" interventions cannot bring meaningful changes in this system, as behavior is determined by resource constraints.

Last but not least, the capacity of even basic bots to influence public opinion, provided their messages are perceived as widely endorsed, presents a cause for concern. With the recent advent of generative AI, data is of crucial importance, since abundant and high-quality data is needed to believably imitate the behavior of real people. This point also connects with the social norm vignettes, where it was shown that subjects are highly averse to sharing their data with businesses. Therefore, it is crucial for policymakers to implement measures that restrict the ability of artificial agents to influence human decisions. This includes restrictions on their ability to masquerade as real individuals and their capacity to generate seemingly authentic content.

This work underscores the imperative for stringent and well-thought-out regulations governing digital spaces. The utmost importance of data in our lives demands policymakers' close attention in order to ensure that only the appropriate actors have access to personal data, and that they only use it for appropriate and prosocial reasons. Artificial agents also have to be limited to not abuse the need of people to conform and belong to a group, otherwise they can be used to steer public opinion. It is understandably difficult for policymakers to keep pace with rapid technological and societal changes, but this work aims to provide some much-needed perspective on the issue.

Future research directions should extend the examination of social norms and conformity to diverse cultural contexts, particularly non-Western settings, which may exhibit distinct attitudes towards these issues. The method by Krupka and Weber (2013) as used here for also identifying perceived motivations behind actors and decisions should also be further developed to account for the major factors that are considered by survey participants. The exploration of social conformity dynamics in varied digital environments and through different levels of ”humanization” of AI entities is also recommended. Extending this line of inquiry towards conformity to a perceived authority could also prove to be fruitful and generate a meaningful contrast to conformity to a majority.

These challenging yet rewarding research projects have offered a thorough experience covering all phases of research, from the idea's inception to sharing the findings, leading to significant personal and professional growth. The interdisciplinary nature of this work brought me into contact with a wide range of views, greatly broadening my understanding of complex issues.

In conclusion, this dissertation sought to dissect the interplay between economics, social norms, decision-making, and conformity, aiming to enrich the academic discourse and offer insights into the ever-evolving digital landscape. Through the delineation of these four projects, I hope to have made a significant contribution to both scholarly literature and the broader understanding of contemporary societal shifts.

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