Essays on Information and Knowledge in Microeconomic Theory

DISSERTATION

zur Erlangung des akademischen Grades

doctor rerum politicarum

(Doktor der Wirtschaftswissenschaft)

eingereicht an der

Wirtschaftswissenschaftlichen Fakultät

der Humboldt-Universität zu Berlin

von

Friederike Julia Heiny, M.Sc.

Präsident der Humboldt-Universität zu Berlin:
Prof. Dr. Peter Frensch (kommissarisch)
Dekan der Wirtschaftswissenschaftlichen Fakultät:
Prof. Dr. Daniel Klapper

Gutachter: 1. Prof. Dr. Anja Schöttner
2. Prof. Dr. Roland Strausz

Tag des Kolloquiums: 13.09.2022

Acknowledgements

First and foremost, I am very grateful to my supervisors, Anja Schöttner and Roland Strausz, for their support, advice and guidance. The insightful discussions on each of the essays made this thesis possible.
Secondly, I benefited tremendously from the cooperation with my co-authors Tianchi Li, Anja Schöttner and Michel Tolksdorf. I am proud of the papers we created and thankful to them for pushing the boundaries.
During this thesis I received helpful input from a group of PhD students, postdocs and professors in Berlin. Particularly, I want to thank Pio Baake, Tobit Gamp, Maren Hahnen, Radosveta Ivanova-Stenzel, Harvey Upton and Ran Weksler for taking the time to discuss my work in-depth and giving me and my co-authors valuable comments. At Tel Aviv University Zvika Neeman hosted and supported me during and after my stay which I am much obliged to. I thank Regine Hallmann, Viviana Lalli, Kristin Schwier, Myrna Selling and Sandra Uzman for their administrative support.
I started my PhD at the graduate center of the DIW and later joined the BDPEMS. The time with my fellow PhD students and the lasting friendships that formed in the past years made this an unparalleled experience. I especially thank Pia Hüttl, Viola Kuzmova and Jan Stede for their continuous support, their friendship and the amazing dinners.
Last but not least, I am indebted to my family and friends. While I cannot name all of them, I am especially thankful to my parents, Andrea and Manfred, my grandpa, my support network from Tübingen, Tina and above all Nick for their love and unwavering faith in me.

Berlin, February 2022

Friederike Julia Heiny

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Abstract

The dissertation consists of three independent chapters that help to understand how knowledge and information is used in microeconomic theory. While Chapter 1 contributes specifically to the literature on behavior-based price discrimination, Chapters 2 and 3 contribute to the literature on knowledge transfers in organizations.

In **Chapter 1**, we study a duopoly model of behavior-based pricing where consumers decide on their data privacy. Contrasting two data environments, we find unique equilibria for each. In an open data environment, all consumers reveal their data. Firms price discriminate causing welfare losses due to poaching. In an exclusive data environment, consumers anonymize, prices are uniform and the market is efficient. We test these contrasting predictions in an experiment. In the open data treatment, subjects predominantly act as predicted. In the exclusive data treatment buyers initially share data but adjust towards anonymization, when sellers start to use poaching strategies.

In **Chapter 2**, we study a model of an organization engaging in knowledge-intensive production. The organizational designer hires workers endowed with knowledge to solve problems whose types are ex ante unknown. The designer determines whether workers produce individually or as a team. As a team, workers can communicate and share their knowledge, while when working individually they can only use their own knowledge. This chapter focuses on the coordination issues that arise in designing the production. We find that teamwork is optimal when knowledge spillovers are sufficiently high. Particularly, when knowledge spillovers are perfect or all problem types are equally likely, self-managed teams arise as a special form of teamwork.

In **Chapter 3**, I explore a dynamic model with a moral hazard problem and knowledge transfer. A principal hires two risk-neutral, wealth-constrained agents to each perform an individual task in a project. Before they address their tasks, the agents can decide to transfer knowledge that increases the task-related productivity of the knowledge receiver. The one-sided knowledge transfer is costly for both. I find that the principal can induce a knowledge transfer with or without commitment power through a joint performance signal. It is not clear that commitment is always better, even though with commitment the first-best allocation can be achieved.

Zusammenfassung

Die Dissertation besteht aus drei unabhängigen Kapiteln, die helfen zu verstehen, wie Wissen und Informationen in der Mikroökonomik verwendet werden. Während Kapitel 1 speziell zur Literatur über verhaltensbasierte Preisdiskriminierung beiträgt, tragen Kapitel 2 und 3 zur Literatur über Wissenstransfer in Organisationen bei.

In **Kapitel 1** untersuchen wir ein Duopolmodell, bei dem die Firmen ihre Preise basierend auf dem Verhalten der Konsumierenden setzen und die Konsumierende über den Schutz ihrer Daten entscheiden. Wir betrachten zwei verschiedene Ansätze bezüglich der Handhabung von Konsumentendaten und ermitteln in jedem Ansatz ein eindeutiges Gleichgewicht. Wenn die Daten beiden Firmen zur Verfügung stehen, geben alle Konsumierende ihre Daten preis. Die Firmen nutzen die Daten der Konsumierenden, um bei der Preisgestaltung zu diskriminieren, was zu Wohlfahrtsverlusten aufgrund von Abwerbung führt. Wenn die Daten exklusiv der Firma zur Verfgüng steht, bei der ein/ eine Konsument:in gekauft hat, geben die Konsumierenden ihre Daten nicht preis. Die Preise sind einheitlich und der Markt ist effizient. Wir testen diese gegensätzlichen Gleichgewichte in einem Experiment. In dem Open-Data-Ansatz verhalten sich die Probanden:innen überwiegend wie in der Theorie vorhergesagt. In dem Exclusive-Data-Ansatz teilen die Probanden:innen zunächst ihre Daten. Sobald jedoch Abwerbungsstrategien verwendet werden, anonymisieren sie sich.

In **Kapitel 2** untersuchen wir ein Modell einer Organisation, die eine wissensintensive Produktion betreibt. Der/ die Organisationsdesigner:in stellt Mitarbeitende ein, die über Wissen verfügen, das sie zum Lösen von Problemen verwenden, deren Art ex ante unbekannt ist. Der/ die Designer:in bestimmt, ob die Mitarbeitenden einzeln oder im Team arbeiten. Im Team können die Mitarbeitenden kommunizieren und ihr Wissen teilen, während sie bei Einzelarbeit nur ihr eigenes Wissen nutzen können. Dieses Kapitel konzentriert sich auf die Koordinationsprobleme, die bei der Gestaltung der Produktion auftreten. Wir stellen fest, dass Teamarbeit optimal ist, wenn der Wissens-Spillover ausreichend hoch ist. Insbesondere dann, wenn der Wissens-Spillover perfekt ist oder alle Problemarten gleich wahrscheinlich sind, entstehen selbstorganisierte Teams als spezielle Form der Teamarbeit.

In **Kapitel 3** untersuche ich ein dynamisches Modell mit einem Moral-Hazard Problem und der Option auf einen Wissenstransfer. Ein/ eine Prinzipal:in stellt zwei risikoneutrale Agenten:innen ein, die über ein eingeschränktes Vermögen verfügen. Die

Agenten:innen übernehmen jeweils eine Aufgabe, die Teil eines gemeinsamen Projekts ist. Bevor sie an ihren Aufgaben arbeiten, können die Agenten:innen entscheiden, ihr Wissen zu teilen. Durch einen Wissenstransfer steigt die Produktivität des Empfangenden von Wissen bezüglich der Aufgabe. Der Wissenstransfer ist einseitig und für beide mit Kosten verbunden. Dadurch das der/ die Prinzipal:in ein Signal zur gemeinsamen Leistung der Agenten:innen erhält, kann er/sie ihnen einen Anreiz geben, ihr Wissen zu teilen. Es existieren optimale Verträge sowohl, wenn der/ die Prinzipal:in verbindlich zu Beginn des Spiels einen Vertrag anbieten kann als auch wenn er/ sie das nicht kann. Es ist nicht eindeutig klar, dass es immer besser ist, wenn der/ die Prinzipal:in verbindlich einen Vertrag zu Beginn des Spiels anbieten kann.

Introduction

"The Master said, Yu, shall I teach you about knowing? To regard knowing it as knowing it; to regard not knowing it as not knowing it – this is knowing."
– Confucius, Analects 2.17 (translated by Brooks and Brooks (1998)).

"Knowledge is power. Information is liberating. Education is the premise of progress in every society, in every family."
– Kofi Anan, Address to World Bank Conference 'Global Knowledge 1997'.

Knowledge and information are essential to any economic system, even more so in the age of data and digitalization. On a macroeconomic level, knowledge is a driver of value creation and therefore also of economic growth. Knowledge as an input factor does not become scarce nor does it suffer from diminishing returns as opposed to physical inputs. On a microeconomic level, companies are in need of skilled workers. The demand for skilled workers increases steadily, while the skills gap is growing (Bundesministerium für Wirtschaft und Klimaschutz, 2021, International Labour Organization, 2021). Thus, rendering education, further training and upskilling necessary to close the gap and resolve the shortage of skilled workers. In today's digital economy, tech companies such as Apple, Microsoft, Alphabet, Meta and Alibaba, made a business out of gathering information about individuals through collecting and analyzing their online data (UNCTAD – United Nations Conference on Trade and Development, 2021). The economic importance of data and information for businesses was addressed by Hal Varian and Carl Shapiro as early as 1998 in their book called fittingly *"Information Rules"*. All these points indicate the relevance and far-reaching impact of knowledge and information today.

The three chapters of this thesis consider the role of knowledge and information[1] in theoretic microeconomic models. The value of knowledge and information in itself is regarded, as well as how knowledge and information can be used to create value. The focus of the distinct models lies particularly on the transfer and application of knowledge and information. Each chapter can be read as a self-contained paper, in which a common situation from day-to-day life is analyzed in a microeconomic model. Taken together the chapters illustrate the wide range of situations in which knowledge and information take center stage and thus reveal the importance of information and knowledge in our daily lifes. While Chapter 1 examines the decision of individuals to share information with a company and how this information is used by the company, Chapters 2 and 3 analyze knowledge sharing between workers within organizations and how it impacts the structure and contracts of organizations. Throughout this thesis my co-authors and I studied the impact of knowledge or information sharing on companies, consumers as well as employees and their co-workers. Subsequently, I describe the role of information or knowledge in each chapter with more (technical) detail.

In Chapter 1, my co-authors, Tianchi Li and Michel Tolksdorf, and I look at a situation that happens to everyone on a daily basis: One visits a website and immediately is asked whether one accepts the use of cookies.[2] Through the use of cookies, a website can access certain information and data of visitors which can be used e.g. to personalize advertisement to individual preferences or to adjust pricing. In Chapter 1, we are interested in the latter utilization of data and information. With the help of a game-theoretic model, we analyze a market with two companies that offer the same product and compete for consumers via prices which can be based on information about consumers. In the model we focus on one piece of information, consumer's purchasing history, instead of considering a set of data that is contained in an actual cookie. We study the consumer's decision to share this information with the companies, i.e., to accept the use of cookies, as well as the subsequent pricing decision of the companies. The model is a two-period game where a continuum of consumers is uniformly distributed along a Hotelling line and the two companies are located at either end of the line. In the first period, companies offer the good without information about consumers. The consumers decide where to buy the good and whether they disclose the information about their purchase. In the second period, companies offer the good again, however, they now may have information about the consumers previous purchase and can therefore set different

[1]According to Davenport et al. (1998b) information is an easily accessible message with the purpose to have an effect on the receiver's actions, behavior or judgement. Information is one step up from data, which are objective facts without interpretation or purpose. Knowledge on the other hand is broader. Davenport and Prusak describe it as "fluid mix of framed experience, values, contextual information, and expert insight [...]".

[2]Due to the General Data Protection Regulation of the European Union, websites must now ask you to share your data and information before they can collect and use it.

prices for loyal customers, new customers and consumers they want to poach.[3] In our model, we examine what happens under two distinct data sharing rules. In an open data environment, the competing firms both receive the information about consumer's purchase history, if consumers decide to disclose this information. Thus, firms compete on symmetric information. This data environment shows potential outcomes of an open data policy.[4] In an exclusive data environment, consumers' information is only shared with the company that the consumer bought from. We analyze the theoretic model and conduct a laboratory experiment to get a more realistic assessment of our theoretic results. We find that the willingness to share information depends on who receives them in both our theoretic model and the laboratory experiment, though the differences for the distinct data environments are more pronounced in the theoretic results. This chapter shows a possible utilization of consumer information and the strategic aspects of transmitting data for e-commerce.

Chapters 2 and 3 leave aside the competitive environment and instead focus on sharing knowledge between co-workers. Both chapters examine the same situation within organizations: Workers on a team are assigned to their individual tasks, however, they have the option to cooperate by sharing their knowledge with a co-worker, which increases the prodcutivity of the workers who receive knowledge. An example for this is a project team at a consultancy where each team member has to work on their own tasks. However, when a team member faces a problem they can ask for their co-workers' experiences and expertise. This knowledge can help them to solve the problem. Chapters 2 and 3 address the coordination and incentive problems, respectively, involved in such situations.

In Chapter 2 my co-author Anja Schöttner and I study under which conditions a company in the knowledge economy wants their employees to work in teams and cooperate by sharing knowledge. The task of each worker is to solve a problem which they can do by working alone or as a team. When they try to solve a problem alone only their own knowledge is available to them. When they work as a team, workers can ask their co-worker for help and learn from them. In such interactions between workers both sender and receiver of knowledge can benefit. While the receiver directly gains from the knowledge of the sender, the sender may be able to learn from the interaction through knowledge spillovers. Thus, when working as a team not only their own knowledge is avaiable to a worker but also the knowledge of their co-worker. However, as in real life, knowledge sharing is not perfect. Workers may not be able to learn from each other when their background is too dissimilar or when it is too similar so that the benefits from knowledge sharing are marginal. Therefore, the conditions under which sharing knowledge is beneficial depend on the knowledge of the workers. We find that for individual work a company should hire workers with

[3] This kind of price discrimination has been observed in online retailing by Mikians et al. (2012, 2013).

[4] Such an open data policy has already been discussed in the European Union (European Commission, 2020).

the same knowledge background, while for teamwork a company should hire workers with different knowledge backgrounds so they can benefit from working in a team. A company chooses teamwork over individual work, when knowledge spillovers in the interaction between workers are high. This way, both workers can benefit from sharing knowledge.

In Chapter 3, I study how managers can induce employees to share their knowledge with co-workers, thus increasing the co-workers' productivity. While the knowledge spillovers in Chapter 2 allowed a two-sided knowledge transfer up to a certain degree, the knowledge transfer in this model is only one-sided. Nevertheless, sharing knowledge is costly for both parties. The sender incurs costs due to the time and effort it takes to explain something to their co-worker, the receiver of knowledge needs to put effort into understanding and learning. Therefore, the workers may not be motivated to share knowledge on their own accord. I find that managers can motivate workers to share knowledge due to a joint performance signal, even though they have no verifiable information on the knowledge transfer. That is, the manager evaluates the workers' performance based on a team outcome and can therefore provide workers with an incentive to share knowledge. In Chapters 2 and 3 we regard knowledge as a central factor for production and learn about the value of employees' knowledge for the organization they work for.

As researchers we are in the knowledge business. We ask questions to which we do not know the answer. We apply what we know to the problem at hand, we get new information and create knowledge. As a final step we share our knowledge in research papers. This thesis conveys what my co-authors and I learned and know from the different research projects.

Chapter 1

We Value Your Privacy: Behavior-based Price Discrimination Under Endogenous Privacy

1.1 Introduction[5]

With an increased capability to process big data and the passing of EU's General Data Protection Regulation (GDPR), behavior-based price discrimination and consumer privacy have become a hot topic. Firms use consumers' data to price discriminate between them. The first major web experiment of behavior-based price discrimination was conducted by Amazon as early as 2000 (Streitfeld, David, 2000). The company discriminated between consumers based on the number of previous purchases at Amazon. Since then consumers' (private) data has been used for behavior-based pricing in online retailing. Mikians et al. (2012, 2013) find evidence for price and search discrimination in e-commerce based on geographical location and consumer's budget in an online field experiment.

A lot has changed in the field of data protection and privacy since Amazon's experiment. Particularly, the passing of the GDPR in May 2018 was a major breakthrough for privacy protection. In accordance with the regulation, consumers can now decide whether to allow websites to access their personal information contained in cookies (Parliament and Council of the European Union, 2016). Cookies are placed by websites to track and record information about previous visits and online activities.[6] The collected data are used by online retailers to make personalized offers in line with behavior-based pricing. The GDPR gives consumers control over their personal information by having a choice to opt-out. By denying cookies, consumers stay anonymous and cannot be identified (as previous customers). Conversely, when consumers allow a firm to access their cookies, they can be identified and targeted with customized prices. This choice to opt-out allows consumers to act strategically. Through the GDPR, consumers' data are exclusively accessible to one retailer at a time. If that retailer plans on distributing consumers' data to third parties, consumers have to explicitly consent.

In this paper, we contrast two different data policies, one that is akin to the GDPR and one where data sharing among firms is mandated. The latter is referred to as an open data environment, whereas, the former is an exclusive data environment, in which only the firm that a consumer bought from receives the consumer's data. We use a behavior-based price discrimination model à la Fudenberg and Tirole (2000) and include an endogenous privacy decision of consumers to study the two aforementioned data environments.[7] We address the following questions: How do consumers react to behavior-based price discrimination when their privacy choice is

[5]This chapter is joint work with Tianchi Li and Michel Tolksdorf. Financial support by Deutsche Forschungsgemeinschaft through CRC TRR 190 is gratefully acknowledged. We thank discussants at BiGSEM Workshop, seminar at UC Louvain and 12th PhD Workshop at Collegio Carlo Alberto, Turin, as well as, participants at workshops and seminars in Berlin, Bielefeld, Delhi, Thessaloniki, Turin, and Tutzingen, EEA Virtual Conference, and ESA Conference.

[6]Throughout this paper, we use the term "cookie" to refer to information about past purchases only.

[7]The European Commission explores the idea of business-to-business data sharing in a recent strategy proposal (European Commission, 2020).

endogenous? How do firms change their pricing strategy? And how does consumers' and firms' behavior differ in the two data environments?

In the first part of this paper, we develop a theoretical model of behavior-based pricing with consumers' endogenous privacy choice. We solve our theoretical model for pure-strategy equilibria that determine consumers' strategy concerning their privacy and firms' price setting. In the second part, we test our theoretical results in a laboratory experiment with human subjects taking the role of buyers and sellers. We explore whether subjects follow our predicted strategies. In the experiment, we want to observe whether consumers act rationally in their privacy decision since previous experimental literature has shown that subjects value their data privacy in itself and therefore make behavioral decisions when presented with the choice to reveal data (Acquisti et al., 2016, Schudy and Utikal, 2017). Both aspects of the analysis are important to comprehend how firms adapt their pricing to different data environments and to understand how this changes consumers' behavior towards their data privacy. The theoretical analysis gives us an insight on firms' and consumers' optimal behavior, while the experiment provides evidence of actual consumer behavior. With our research we also contribute to the EU's debate about a policy that mandates data sharing among firms.

Following Fudenberg and Tirole (2000), we build on the Hotelling (1929) linear city model with two competing firms and a continuum of consumers. We consider a two-period game, where a consumer buys one unit of a non-durable product in each period from one of the firms. In the first period, firms set identical prices for all consumers with no information about consumers' preferences. Consumers then decide from which firm to buy and whether to accept the use of cookies. In the second period, based on consumers' strategy, firms can set different prices and consumers, again, decide where to buy. In the open data environment, firms share the obtained information with each other.[8] In the exclusive data environment, given consumers accept cookies, only the supplier that a consumer has bought from can access the private information. To realize our experiment, we only need to discretize the number of consumers in the market. Hence, the experiment closely resembles our theoretical model. In order to further explore consumers' behaviour, we have subjects play the market game for 20 consecutive rounds, such that we can control for learning effects. As additional measures to learn more about our subjects, we include a task on strategic thinking to control for subjects' cognitive abilities and a survey on their privacy concern.

In the open data environment, when consumers' data are available to both competitors, consumers in equilibrium choose to reveal their data, in order to increase competition between firms.[9] Firms use the data to price discriminate between loyal consumers and consumers, who previously purchased from the competitor. We can

[8] Ghosh et al. (2015) show a concrete example in which information is shared via cookie matching.

[9] Ali et al. (2020) and Casadesus-Masanell and Hervas-Drane (2015) also support this result in their theoretical models.

confirm this result with experimental evidence from the open data treatment. Buyers predominantly allow tracking of their past purchase, which gives sellers the chance to use behavior-based pricing. We observe that sellers use poaching prices as reward for accepting cookies that are lower than prices for loyal or anonymous customers.

In the exclusive data environment, when consumers' data are only available to the respective firm they bought from, consumers are individually best off by maintaining their privacy. Given that data is exclusive to firms, consumers are individually worse off by revealing their data because firms can use their data to price discriminate without intensifying competition. Yet, if consumers collectively coordinated to reveal their data, they would improve their outcome.[10] To our knowledge, this is a novel finding in competitive settings with privacy decisions. In our experiment we find that consumers initially share their information readily. However, there is a downwards trend in the cookie sharing rate over time when sellers begin to price discriminate. Buyers adjust accordingly by anonymizing more.

From a theoretical point of view, social welfare is maximal in the exclusive data environment, even though it hurts consumers. In equilibrium, all consumers choose to be anonymous and, therefore, firms set uniform prices. In this equilibrium consumers do not switch between firms. On the other hand, in equilibrium, consumer welfare is larger in the open data environment, because consumers benefit from poaching offers. However, the experimental results exhibit no significant difference in social welfare between treatments. This indicates that an open data environment can be an option to enhance competition between firms without incurring a loss in total welfare. Our theoretical and experimental results show that mandated data sharing among firms leads consumers to share more data to their own benefit, providing an argument in favor of an open data mandate.

1.1.1 Related Literature

Our paper is related to a set of articles in the theoretical and the experimental literature on behavior-based price discrimination and consumer privacy.

The two papers closest to our theoretical research are Ali et al. (2020) and Conitzer et al. (2012). Conitzer et al. (2012) study a monopoly with an outside option where consumers can choose to let the monopolist track their purchases. They find that under free anonymization all consumers choose to do so, which gives the monopolist the highest payoff. Importantly, the introduction of competition raises issues in the handling of the information structure, which leads to our separation of the open and exclusive data environments. As in our paper, consumers have an endogenous privacy choice. However, Conitzer et al. (2012) do not study a competitive situation of behavior-based pricing, where the strategic action of consumers has different implications for pricing. Our focus is on consumers' privacy choice for different data environments, in which we diverge from the theoretical analysis of Conitzer

[10] The privacy choice resembles a multi-player prisoners' dilemma in the exclusive data environment.

et al. (2012). Ali et al. (2020) study how complete consumer control over their data affects personalized pricing in a monopoly as well as under competition. They focus on comparing disclosure channels and analyze consumers sharing rich and simple evidence about their types. In our model we only look at a dichotomous disclosure technique, tracking versus no tracking, but support the same result, that voluntary disclosure amplifies competition.

To our knowledge the only other studies besides Ali et al. (2020) that deal with endogenous privacy choices in a competitive market are Acquisti and Varian (2005) and Casadesus-Masanell and Hervas-Drane (2015). Differing from our paper Acquisti and Varian (2005) only consider two consumer types instead of a continuous differentiation and undifferentiated products. Casadesus-Masanell and Hervas-Drane (2015) consider homogenous goods in a one-period model, where information is provided directly by consumers and not indirectly in form of their purchase history.

Colombo (2016) considers a set-up of incomplete information sharing in a duopoly case similar to our exclusive data environment (in Section 1.2.2.2). Colombo uses a fixed parameter as share of anonymous consumers and does not consider consumers' endogenous privacy choice. Belleflamme and Vergote (2016) employ a similar parameter as the precision of the tracking technology in a monopolistic setting with endogenous privacy choices as in Conitzer et al. (2012) but without repeat purchases. The main point of our study, however, is to analyze the strategic decisions of consumers in a duopolistic setting with repeat purchases over two periods. Other papers that are also concerned with price discrimination and exogenous privacy are Esteves (2014) and Liu and Serfes (2004).

Choi et al. (2019), Montes et al. (2018) and Taylor (2004) extend the idea of price discrimination and privacy to include a data broker. Montes et al. (2018) consider a duopoly with a costly privacy choice for consumers. They focus on a data broker who sells consumers' data to competing firms. One of their main results is that information is usually only sold to one of the firms. We feature this as the exclusive data environment, where we observe a higher producer surplus than in the open data environment. Choi et al. (2019) study the stage of data collection and show that either due to a monopolistic platform or due to the emergence of data brokerage an excessive amount of data is collected to the detriment of consumers.

Extensive reviews of the literature on behavior-based price discrimination in general and the economics of privacy can be found in Acquisti et al. (2016), Armstrong (2006), Fudenberg and Villas-Boas (2006) and Esteves et al. (2009).

The experimental analysis of behavior-based pricing under endogenous privacy relates to two branches in the experimental literature. Firstly, the basic structure and procedure are related to spatial competition experiments. We extend the existing literature on behavior-based price discrimination and spatial competition with location choice experiments. Behavior-based pricing experiments have been conducted by Brokesova et al. (2014) and Mahmood (2014). Brokesova et al. (2014) computerize the buyer's side, which we do not. Mahmood (2014) only considers two fixed locations for buyers, whereby the experimental market rather resembles a Bertrand market with differentiated products than a spatial competition. We employ a behavior-based pricing experiment similar to those two but introduce features from spatial competition with location choice experiments by Barreda-Tarrazona et al. (2011) and Camacho-Cuena et al. (2005), which is how we transform the theoretical set-up into an experimental set-up with treatments corresponding to the two data environments.

Secondly, we introduce privacy and data sharing elements. Similar issues have been studied before, but to our knowledge not in the context of an explicit market experiment. Acquisti et al. (2013) identify a considerable gap between willingness to accept disclosure of private information and willingness to pay for the protection of private information. To alleviate this issue we renounce enforcing a default option on privacy, assuming disclosure and protection are both costless. Beresford et al. (2012) and Preibusch et al. (2013) find that subjects have a remarkably low willingness-to-accept for giving up their privacy and are not acting on their stated privacy decisions when protection of privacy is costless. This finding contrasts Tsai et al. (2011) who find that subjects act on websites' certified privacy protection qualities when shopping online. They suggest that subjects might in fact be willing to pay premiums for privacy protection.

Schudy and Utikal (2017) find that subjects' willingness to share personal information decreases when the number of recipients of said information increases. Between our open and exclusive data treatments the number of recipients varies. In support of their findings, we observe a higher willingness to share information in the early rounds of the exclusive data treatment. In later rounds we observe more information sharing in the open data treatment, which is in line with our theoretical predictions. This indicates that participants see the privacy decision as a strategic choice, which allows them to face lower prices.

We contribute to the literature by focusing on consumers' endogenous privacy decisions in competitive markets under a set of different information schemes. Combining a theoretical model with an experiment is a novel approach to answer our research questions.

The rest of the article is structured as follows. In Section 1.2, we develop our theoretical model and analyze the two different data environments. In Section 1.3, we present our experimental set-up and the results from our analysis of seller and buyer behavior. Section 1.4 concludes the article.

1.2 Theory

In this part of the paper we present our theoretical model and the results from the analysis. First, we introduce the model set-up. Next, we analyze our theoretical model under the *open data environment*, where information about previous purchases is given to both firms. This is followed by the analysis of the *exclusive data environment*, where only the firm that a consumer has bought from in the first period can access consumers' cookies. Last but not least, we state welfare results from the theoretical model.

1.2.1 Model

We consider a set-up following Hotelling (1929), where a line segment of length $\bar{\theta}$ spans a product characteristic space. Along the line, consumers are uniformly distributed with a density of $\bar{\theta}^{-1}$, i.e., we assume a consumer mass of 1. A consumer's type is denoted by $\theta \in \left[0,\ \bar{\theta}\ \right]$, such that θ serves as the consumer's preferred variety of a good.

There are two firms each producing a variant of the same good at constant marginal costs normalized to zero; fixed costs are neglected. We normalize production costs because we do not focus on firms' production processes. Firm A is located at the left end of the line segment, while firm B is placed at the right end. The firms compete for two periods, $t = 1, 2$.

In each period, consumers buy one unit of the good either from firm A or B, $b_t \in \{A, B\}$, i.e., we assume that the good's valuation is large enough to make sure each consumer buys one unit in each period. No outside option is available. Considering a consumer located at $\hat{\theta}$, their utility is given by $U_A = v - p_A - \hat{\theta}$ or $U_B = v - p_B - (\bar{\theta} - \hat{\theta})$, depending on their purchasing decision. We assume consumers' unit transportation cost to be normalized to one. Consumers' valuations, v, are the same over time for all consumers. Their rationale is to maximize their utility. We do not take discounting into account to simplify the analysis.

On top of the buying decisions, b_t, consumers also decide whether to accept the use of cookies, $q \in \{0, 1\}$, in the first period. We use the term "cookies" as proxy for a consumer's buying decision in the first period, which is revealed to a company if $q = 1$. In that case, a firm is able to identify a buyer from period $t = 1$ and can thus set a different price in the upcoming period. Consumers have the option to act strategically with regards to revealing information. In the literature, it is often assumed that generating privacy involves some costs (Conitzer et al., 2012, Montes et al., 2018). However, Loertscher and Marx (2020) show that the act of providing data can even be costly for consumers. We refrain from assumptions on privacy costs to keep the theoretical predictions clean from any of these effects. This is important for the experiment, because we can then observe subjects' unbiased privacy concern.

In the first period, competing firms set price p_1^i, where $i, j = A, B$ and $i \neq j$. In the second period, pricing is more involved. Depending on the preceding cookie choice of consumers, there is a share λ of anonymous consumers who denied the use of their cookies and a share $1 - \lambda$ of identifiable consumers. The shares are derived from the aggregation of consumers' choices regarding their cookies. We assume that λ is common to both firms.

Given a consumer's cookie choice, we differentiate between two data environments, which differ with regards to the number of recipients of consumers' data. The information about consumers' buying decision in the first period is either available to both firms, which we call *open data environment*, or a firm exclusively receives the information, which we call *exclusive data environment.*

In the open data environment, accepting the use of cookies means that both firms can access the information about a consumer's past purchase (contained in the cookie). In the exclusive data environment, accepting the use of cookies means that only the firm a consumer has bought from can access information about a consumer's past purchase (contained in the cookie).

In the open data environment, where both firms can target the competitors' consumers, each firm distinguishes three prices in the second period: $p^i_{2,i}$, is firm i's loyalty price for identifiable consumers who bought from firm i in the first period; $p^i_{2,j}$, is firm i's poaching price for identifiable consumers who bought from j in the first period; and p^i_2, is firm i's new customer price for anonymous consumers who belong to the share λ. The idea of poaching consumers was first explored in Fudenberg and Tirole (2000).

In Section 1.2.2.2, we diverge from the open data environment and assume that only firms that consumers have bought from in the first period can learn about the purchasing history. This alters the pricing strategy considering that firms can no longer set a poaching price $p^i_{2,j}$, since the information needed is not available to them.

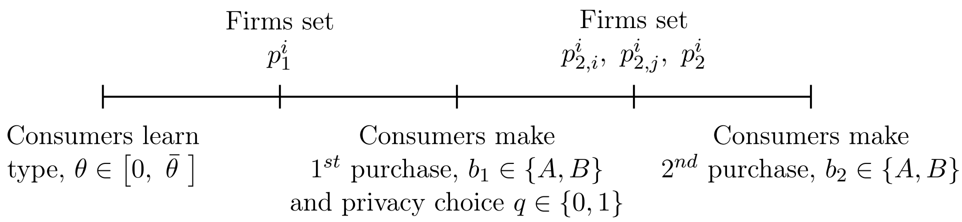


Figure 1.1: Timeline of the game.

Figure 1.1 depicts the timing of the game. At the beginning, each consumer learns their type θ. Then in the first period, firms each set price p^i_1. Afterwards, consumers simultaneously make their purchasing decision, $b_1 \in \{A, B\}$ and their cookie choice, $q \in \{0, 1\}$. In the second period, firms set prices $\mathbf{p_2} = (p^i_{2,i}, p^i_2, p^i_{2,j})$.[11] At the end of the second period consumers again choose to buy from A or B. Finally, consumers receive their utilities and firms earn profits.

We solve for perfect Bayesian Nash equilibria (PBE) in pure strategies. In this context a PBE comprises firm's and consumers' strategy. Firms' strategies contain first- and second-period prices for the respective data environment and their beliefs about consumers' types given their cookie choice.[12] Consumers' strategies contain

[11] There is no poaching in the exclusive data environment, since it is equivalent to inducing $p^i_{2,j} \equiv p^i_2$.
[12] The strategy should also contain second-period prices if firms had set different prices in the first period. This is omitted here for simplicity.

their first purchase and the privacy choice dependent on their type, firms' first-period prices and anticipation of optimal second-period prices and their second purchase dependent on their type and second-period prices.

1.2.2 Endogenous Privacy

In this section we analyze our endogenous privacy model and solve for PBE.[13] The potential equilibria can be categorized into pooling and separating equilibria based on the consumer's cookie choice and their type. In a pooling equilibrium, all consumers make the same cookie choice independent of their type. Firms observe the share of anonymous consumers, λ, and believe this to be identical to the probability to hide data for each consumer. Analogously, $1-\lambda$, corresponds to the probability that each consumer reveals their data. In a separating equilibrium, consumers base their cookie choice on their type. This means that firms can form beliefs over any number of segments of arbitrary length where within each segment consumers either all disclose or all hide their information (due to pure strategy). We consider the two possible equilibrium categories one after another, starting out with deriving possible pooling equilibria. We relax assumptions on pooling, respectively separating, once we identify equilibrium candidates.

1.2.2.1 Open data environment

In the open data environment, both firms receive information about a consumer's previous purchase given the consumer decides to grant access to their cookie. Consumers who did not let firms access their cookies in the first period are anonymous to both firms and are treated as new customers. Therefore, they face prices p_2^A (p_2^B) from firm A (firm B) in the second period. Consumers who revealed information about the purchase in the first period can be recognized by firms and thus are offered different prices in the second period. The prices $p_{2,A}^A$ ($p_{2,A}^B$) are offered by firm A (firm B) for consumers who bought from firm A in the first period, and $p_{2,B}^B$ ($p_{2,B}^A$) are set by firm B (firm A) for consumers who bought from firm B in the first period.

In the second period, based on firms' beliefs, we divide consumers by their privacy choice into identifiable and anonymous consumers. As we begin our analysis under the pooling assumption we can consider two separate Hotelling lines, one for the group of identifiable and one for the group of anonymous consumers. On the anonymous consumers' line, there are λ consumers uniformly distributed. We show that on this line, there exists a marginal consumer, θ_2, who is indifferent between buying from firm A and firm B. The marginal consumer is determined by $v-p_2^A-\theta_2 = v-p_2^B-(\bar{\theta}-\theta_2)$ as

$$\theta_2 = \frac{\bar{\theta}}{2} + \frac{p_2^B - p_2^A}{2}.$$

[13] We restrict our analysis to pure strategy equilibria due to intractability of mixed strategy specifications.

Therefore, consumers with type $\theta \in [0, \theta_2)$ buy from firm A in the second period given they chose to anonymize. Similarly, consumers with $\theta \in (\theta_2, \bar{\theta}]$ buy from firm B.

The other line has a mass of $1-\lambda$ uniformly distributed and identifiable consumers. They are confronted with behavior-based price discrimination. Among the mass of $1-\lambda$ consumers, those who bought from firm A in the first period are given two prices in the second period: $p^A_{2,A}$ as loyalty price set by firm A, and $p^B_{2,A}$ as a poaching price from firm B. Similarly, consumers who bought from firm B in the first period also face two prices now, $p^B_{2,B}$ as loyalty price from firm B, and $p^A_{2,B}$ as a poaching price from firm A.

On A's turf there is a marginal consumer indifferent between buying from firm A at $p^A_{2,A}$ and buying from firm B at $p^B_{2,A}$. They are characterized by

$$\theta^A_2 = \frac{\bar{\theta}}{2} + \frac{p^B_{2,A} - p^A_{2,A}}{2}.$$

Accordingly, on B's turf the marginal customer θ^B_2 is determined by

$$\theta^B_2 = \frac{\bar{\theta}}{2} + \frac{p^B_{2,B} - p^A_{2,B}}{2}.$$

Identified consumers with $\theta \in [0, \theta^A_2)$ and $\theta \in (\theta^B_2, \bar{\theta}]$ are loyal to the firm they bought from in the first period. Contrarily, consumers located at $\theta \in (\theta^A_2, \theta_1)$ and $\theta \in (\theta_1, \theta^B_2)$ are poached by the competing firm, where θ_1 denotes the first-period marginal consumer who is indifferent between buying from A and B.

Figure 1.2 depicts the consumer shares and respective pricing by spanning a rectangle over both lines connected vertically through the share λ under pooling beliefs. The maximization problem of the firms concerning the anonymous consumers

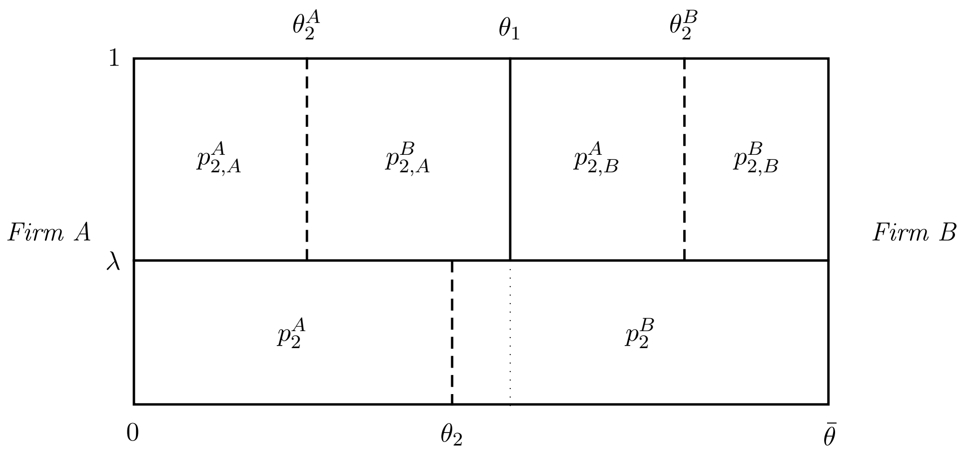


Figure 1.2: Customer segments under open data in $t = 2$.

is given by

$$\max_{p_2^A} \quad \lambda p_2^A \left[\frac{\bar{\theta}}{2} + \frac{p_2^B - p_2^A}{2}\right],$$

$$\max_{p_2^B} \quad \lambda p_2^B \left[\bar{\theta} - \left(\frac{\bar{\theta}}{2} + \frac{p_2^B - p_2^A}{2}\right)\right].$$

From the first-order conditions, we obtain the prices for anonymous consumers $p_2^A = p_2^B = \bar{\theta}$ and the marginal consumer, $\theta_2 = \frac{\bar{\theta}}{2}$.

Among the identified consumers with mass $1 - \lambda$, we have the following maximization problems:

$$\max_{p_{2,A}^A, p_{2,B}^A} \quad (1-\lambda)\left[p_{2,A}^A \theta_2^A + p_{2,B}^A\left(\theta_2^B - \theta_1\right)\right],$$

$$\max_{p_{2,B}^B, p_{2,A}^B} \quad (1-\lambda)\left[p_{2,B}^B\left(\bar{\theta} - \theta_2^B\right) + p_{2,A}^B\left(\theta_1 - \theta_2^A\right)\right].$$

By plugging θ_2^A and θ_2^B into these two equations, we can solve for the prices.

Lemma 1.1 *The set of prices in the second period depend on θ_1 and the parameter $\bar{\theta}$.*

Loyalty prices are given by

$$p_{2,A}^A = \begin{cases} \frac{1}{3}(2\theta_1 + \bar{\theta}) & \text{if } \frac{1}{4}\bar{\theta} \leq \theta_1 \\ \bar{\theta} - 2\theta_1 & \text{otherwise.} \end{cases} \qquad p_{2,B}^B = \begin{cases} \frac{1}{3}(3\bar{\theta} - 2\theta_1) & \text{if } \frac{3}{4}\bar{\theta} \geq \theta_1 \\ 2\theta_1 - \bar{\theta} & \text{otherwise.} \end{cases}$$

Poaching prices are given by[14]

$$p_{2,B}^A = \begin{cases} \frac{1}{3}(3\bar{\theta} - 4\theta_1) & \text{if } \frac{3}{4}\bar{\theta} \geq \theta_1 \\ 0 & \text{otherwise.} \end{cases} \qquad p_{2,A}^B = \begin{cases} \frac{1}{3}(4\theta_1 - \bar{\theta}) & \text{if } \frac{1}{4}\bar{\theta} \leq \theta_1 \\ 0 & \text{otherwise.} \end{cases}$$

New customer prices are $p_2^A = p_2^B = \bar{\theta}$.

Proof. *See Appendix.* ■

Lemma 1.1 shows that if a customer chooses not to share their information in the first period, they will face uniform pricing in the second period under a pooling assumption. However, if they reveal information in the first period, they are confronted with behavior-based prices, including poaching prices offered by the competitive firm in the second period. Lemma 1.1 demonstrates that prices are independent of λ

[14]When $\theta_1 < \frac{1}{4}\bar{\theta}$ it follows that $p_{2,A}^B = 0$, and so Firm A sets $p_{2,A}^A$ such that $v - p_{2,A}^A - \theta_1 = v - (\bar{\theta} - \theta_1)$. Accordingly for firm B.

under pooling. Moreover, the result $p_2^i > p_{2,i}^i > p_{2,j}^i$ holds generally, irrespective of $\theta_1 \in (0, \bar{\theta})$.[15]

In the first period, we look at consumers' endogenous decisions about their cookies. By comparing second-period prices for anonymous consumers to second-period prices for recognized consumers, we can show that prices for anonymous consumers are always higher. Consumers can strategically choose to share their purchasing history in the first period, in order to receive lower prices in the second period. Thus, every consumer discloses their information, which implies that the mass λ of consumers on the anonymous line is zero. Firms form their beliefs accordingly.

Lastly, we consider price setting of firms in the first period. Similar to the second period, there are two separated lines in the first period. For the line of consumers who did not share their cookies, there is a cut-off customer, $\hat{\theta}_1$, who, in the first period, is indifferent between buying from firm A at p_1^A and buying from firm B at p_1^B.[16] It is determined by $\hat{\theta}_1 = \frac{\bar{\theta}}{2} + \frac{1}{2}(p_1^B - p_1^A)$.

On the other hand, on the line of those who shared their cookies in the first period, the marginal customer, θ_1, is defined by the following equivalence,

$$v - p_1^A - \theta_1 + \left[v - p_{2,A}^B - \left(\bar{\theta} - \theta_1\right)\right] = v - p_1^B - \left(\bar{\theta} - \theta_1\right) + \left[v - p_{2,B}^A - \theta_1\right].$$

The equation represents consumers indifferent between buying from firm A at p_1^A in period 1 and afterwards from firm B at $p_{2,A}^B$ in period 2, and buying from firm B at p_1^B in period 1 and then purchasing from firm A at $p_{2,B}^A$ in period 2. Hence, the marginal consumer is given by $\theta_1 = \frac{\bar{\theta}}{2} + \frac{3}{8}(p_1^B - p_1^A)$.

In the first period, firms maximize the overall profits, thus firm A's problem is to maximize the following term with respect to the first-period prices

$$\pi^A = \lambda p_1^A \hat{\theta}_1 + (1-\lambda) p_1^A \theta_1 + \lambda p_2^A \theta_2 + (1-\lambda)\left[p_{2,A}^A \theta_2^A + p_{2,B}^A \left(\theta_2^B - \theta_1\right)\right].$$

Similarly, firm B maximizes

$$\begin{aligned}\pi^B = &\lambda p_1^B \left(\bar{\theta} - \hat{\theta}_1\right) + (1-\lambda) p_1^B \left(\bar{\theta} - \theta_1\right) + \lambda p_2^B \left(\bar{\theta} - \theta_2\right) \\ &+ (1-\lambda)\left[p_{2,A}^B \left(\theta_1 - \theta_2^A\right) + p_{2,B}^B \left(\bar{\theta} - \theta_2^B\right)\right].\end{aligned}$$

From the second-period analysis, we have obtained $p_2^A = p_2^B = \bar{\theta}$ and $\theta_2 = \frac{\bar{\theta}}{2}$. Therefore, the respective third terms in the profit functions do not affect the maximization problem. Solving the maximization problems under consideration of consumers' privacy choices yields our first proposition.

[15] In the special cases of $\theta_1 = 0$ ($\theta_1 = \bar{\theta}$) we would have $p_{2,B}^A = p_{2,B}^B = p_2^A = p_2^B$ ($p_{2,A}^A = p_{2,A}^B = p_2^A = p_2^B$) under pooling.

[16] $\hat{\theta}_1$ is not influenced by second-period prices, because firms maximize their profits by choosing p_2^A and p_2^B which are independent of the first period.

Proposition 1.1 *The prices under open data for the competing firms in both periods are*

$$p_1^A = p_1^B = \frac{4}{3+\lambda}\bar{\theta}, \qquad p_{2,A}^A = p_{2,B}^B = \frac{2}{3}\bar{\theta}, \qquad p_{2,B}^A = p_{2,A}^B = \frac{1}{3}\bar{\theta}.$$

The marginal consumer in the first period is located at $\theta_1 = \frac{\bar{\theta}}{2}$. Consumers' strategy is to disclose data such that $\lambda = 0$ $\forall\theta$. Therefore, we obtain a symmetric PBE in pure strategies.

Proof. *See Appendix.* ■

Proposition 1.1 shows firms' price choices and consumers' privacy choice, λ, in equilibrium. The limit cases of λ reveal an interesting insight. If $\lambda = 1$, which means that none of the consumers grants access to their cookie in the first period, this results in a uniform pricing strategy, $p_1^A = p_1^B = \bar{\theta}$. If on the other hand $\lambda = 0$, which means that all consumers share their information in the first period, we get that $p_1^A = p_1^B = \frac{4}{3}\bar{\theta}$, which is a standard behavior-based pricing strategy. Therefore, for all values of $\lambda \in (0, 1)$, p_1^A and p_1^B represent a mixture of uniform pricing and behavior-based pricing. In equilibrium we find that all consumers choose to reveal their data, $\lambda = 0$, thus firms' prices for anonymous consumers are not realized.[17]

We derive the equilibrium in Proposition 1.1 under pooling beliefs. In the proof of Proposition 1.1, we use a refinement argument, relaxing pooling beliefs, to show that an individual deviation from consumers' cookie choices is not desirable. Now we inspect whether there are alternative equilibria under separating beliefs, where consumers base their cookie choice on their type. We check for potential equilibria in pure strategies. The results are summarized in the following proposition.

Proposition 1.2 *There exists no separating equilibrium in pure strategies in the open data environment. The pooling equilibrium derived above is unique among pure strategies.*

Proof. *See Appendix.* ■

Proposition 1.2 shows that under the open data environment the equilibrium derived in Proposition 1.1, where all consumers reveal their information, is unique. From the results in Propositions 1.1 and 1.2 we gather that an open data environment leads to identical results as in standard behavior-based pricing with exogenous privacy where competitors do not share information (see Fudenberg and Tirole, 2000). Consumers are best off by revealing data, because they can benefit from the lower customized prices in the second period.

[17] Surprisingly, we find the same pricing and privacy choices when consumers are myopic in their first-period purchasing decision, but strategic in their privacy choice. This indicates that the privacy choice absorbs the strategic properties of the first-period purchasing decision. When transportation costs are quadratic we find qualitatively similar pricing choices and the same privacy choices as in the case of linear transportation costs. See Appendix.

1.2.2.2 Exclusive data environment

In this section, we analyze a setting where firms only learn about cookies of customers who actually bought from them. This implies that there is exclusive data in the market, as for example consumers of firm B, might reveal their purchasing history to B, such that B can identify them. However, firm A does not receive the information and therefore, these consumers are anonymous to A. The pricing strategy in the second period is distinct from the open data environment, where three different prices were set by each firm after consumers made a decision regarding their cookie choices. In comparison, in the exclusive data environment firms cannot distinguish between a competitor's customers and their own anonymous consumers. They are just a mass of non-identifiable consumers. This implies that firms cannot set a poaching price to steal consumers from each other. The pricing strategy for the second period only entails a loyalty price, $p^i_{2,i}$, and a new customer price, p^i_2 for $i = A, B$. The first-period pricing is similar to the open data environment and not affected by the difference in the data environment. As before, there is a marginal consumer in the first period, θ_1, who is indifferent between buying from A and B.[18]

In the exclusive data environment, the Hotelling lines cannot be separated as in the open data environment. The reason is that the new customer price serves two functions. Firstly, it is the price for the own consumers who are not identifiable and secondly, it serves as a "poaching price" for competitors' consumers. Figure 1.3 below depicts this clearly, since p^i_2 appears on both lines. Firms want to maximize their profits by choosing prices $p^i_{2,i}$ and p^i_2 for $i = A, B$ in the second period. As before, we start by employing the pooling beliefs. There is a share $1-\lambda$ of consumers who choose to give access to their cookies and a share λ of consumers who hide their cookies, with λ corresponding to the probability of hiding for every consumer. For the share λ of anonymous consumers there is an indifferent customer located at θ_2, who is impartial between buying from A at price p^A_2 and B at price p^B_2. For the identifiable consumers, there is a marginal consumer in each firms' turfs: $\theta^{A'}_2$ is indifferent between buying from A as identifiable consumer and buying from B as anonymous customer, whereas $\theta^{B'}_2$ is the respective cut-off value on B's turf. Figure 1.3 shows this customer segmentation and price setting in a rectangle, where the two horizontal lines are again connected by λ.

From Figure 1.3 we derive the maximization problems of the firms in the second period:

$$\max_{p^A_2, p^A_{2,A}} \pi^A_2 = \max_{p^A_2, p^A_{2,A}} \lambda p^A_2\ \theta_2 + (1-\lambda) p^A_{2,A}\ \theta^{A'}_2 + (1-\lambda) p^A_2 \left(\theta^{B'}_2 - \theta_1\right),$$

$$\max_{p^B_2, p^B_{2,B}} \pi^B_2 = \max_{p^B_2, p^B_{2,B}} \lambda p^B_2 \left(\bar{\theta} - \theta_2\right) + (1-\lambda) p^B_{2,B} \left(\bar{\theta} - \theta^{B'}_2\right) + (1-\lambda) p^B_2 \left(\theta_1 - \theta^{A'}_2\right).$$

[18] The analysis is similar to Colombo (2016). However, the essential difference is that he treats λ as an exogenous parameter, while we use it as proxy for consumers' endogenous decisions regarding their cookies.

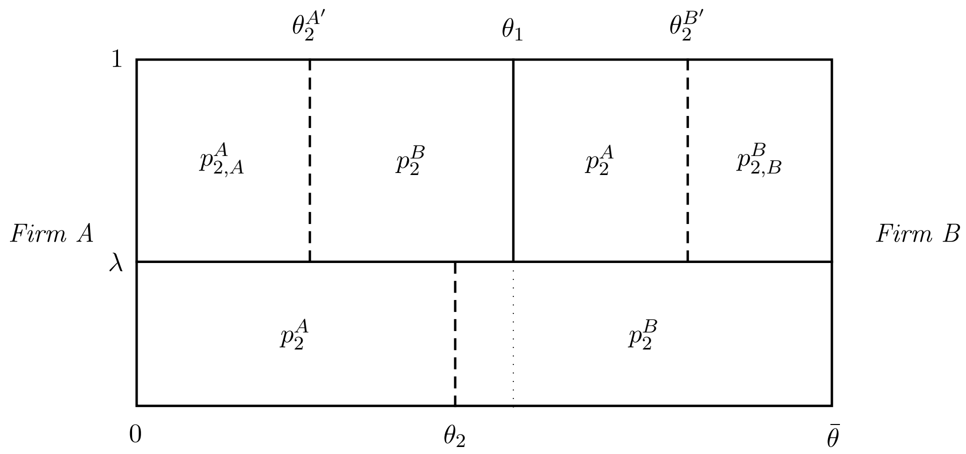


Figure 1.3: Customer segments under exclusive data.

Lemma 1.2 *Solving the maximization problems, we can derive the following prices for the second period. For firm A:*

$$p_2^A(\lambda, \mathbf{p_1}) = \frac{(9 - 2\lambda + 5\lambda^2)\bar{\theta} - 4(3-\lambda)(1-\lambda)\theta_1}{3\left[4 - (1-\lambda)^2\right]},$$
$$p_{2,A}^A(\lambda, \mathbf{p_1}) = \frac{(3 + 10\lambda - \lambda^2)\bar{\theta} + 2(3-\lambda)(1-\lambda)\theta_1}{3\left[4 - (1-\lambda)^2\right]}.$$

For firm B:

$$p_2^B(\lambda, \mathbf{p_1}) = \frac{(-3 + 14\lambda + \lambda^2)\bar{\theta} + 4(3-\lambda)(1-\lambda)\theta_1}{3\left[4 - (1-\lambda)^2\right]},$$
$$p_{2,B}^B(\lambda, \mathbf{p_1}) = \frac{(9 + 2\lambda + \lambda^2)\bar{\theta} - 2(3-\lambda)(1-\lambda)\theta_1}{3\left[4 - (1-\lambda)^2\right]}.$$

Proof. *See Appendix.* ■

The second-period prices in this case are not only dependent on the first-period prices, as is the case in the analysis of the open data environment, but also depend on λ as the share of buyers who choose to be anonymous.

All prices increase with λ, i.e., the more likely consumers are to hide their cookies, the higher are not only the new customer prices but also the loyalty prices of both firms. This always holds for $\frac{1-\lambda}{3-\lambda}\bar{\theta} \leq \theta_1 \leq \frac{2}{3-\lambda}\bar{\theta}$. Under this condition, loyalty prices are larger or equal to new customer prices.[19]

Figure 1.4 depicts loyalty and new customer prices of firm A for $\bar{\theta} = 1$ and $\theta_1 = \frac{1}{2}$. At $\lambda = 0$, firms set symmetric prices with $p_2^A = p_2^B = \frac{1}{3}$ and $p_{2,A}^A = p_{2,B}^B = \frac{2}{3}$. The price setting corresponds to poaching and loyalty prices in the open data environment, respectively. Given $\lambda \to 1$[20] all prices converge to $\bar{\theta} = 1$, the uniform pricing strategy. There is no price discrimination in this case since there is no information available.

[19]When we derive first-period prices we show that the market is separated symmetrically between the firms such that the condition holds.
[20]Notice that for $\lambda = 1$, the loyalty prices are no longer contained in the maximization problems.

The graph shows that prices are convex, increasing in λ and within the range of $\lambda \in [0, 1)$ loyalty and new customer prices do not cross. Therefore, even though the new customer prices increase with λ, they are always below the loyalty prices. In Figure 1.4, we observe a situation that is similar to the prisoner's dilemma. Consumers face the highest prices when λ approaches 1. When $\lambda = 1$ only new customer prices are realized and correspond to uniform prices of 1. On the other hand, if consumers were to decide to hide their information with probability $\lambda = 0$, this would lead them to a price of $\frac{2}{3}$ which is below 1. This means, if consumers can coordinate on putting zero probability on anonymizing, they would all gain. However, consumers have an incentive to deviate to stay anonymous with a positive probability, since for any $\lambda \in (0, 1)$ they face a new customer price below the loyalty price. This incentive leads all consumers to anonymize.

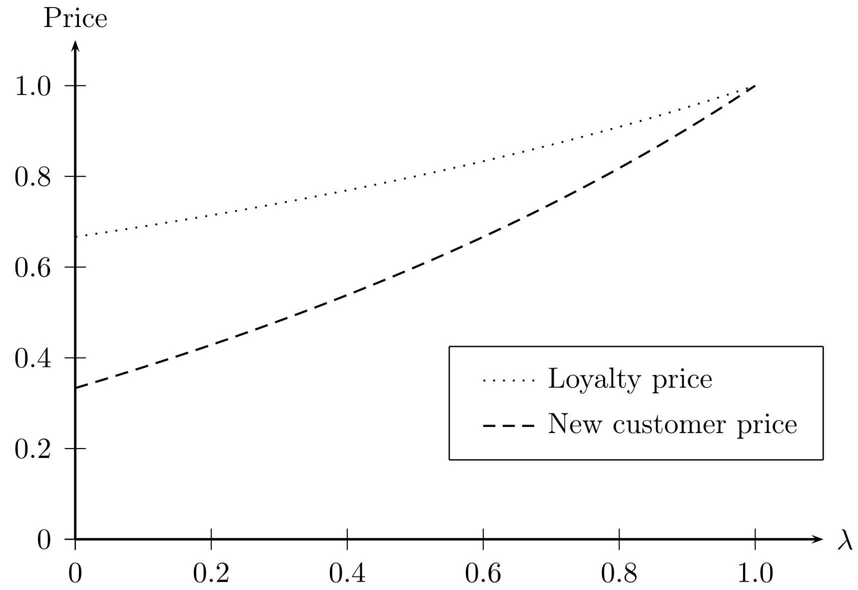


Figure 1.4: Prices of Firm A for $\bar{\theta} = 1$ and $\theta_1 = 0.5$.

Because consumers' best strategy is to hide their cookies with probability $\lambda = 1$, the two periods in this game are independent of each other. Therefore, in the first period firms solve the following maximization problems:

$$p_1^A = \arg\max_{p_1^A} \ \pi^A = p_1^A \theta_1 + \pi_2^A,$$
$$p_1^B = \arg\max_{p_1^B} \ \pi^B = p_1^A (\bar{\theta} - \theta_1) + \pi_2^B,$$

where $\theta_1 = \frac{p_1^B - p_1^A + \bar{\theta}}{2}$ for $\lambda = 1$.

Proposition 1.3 *In the exclusive data environment, final prices all coincide with the uniform pricing strategy, such that prices on the first and second period are $\bar{\theta}$. Therefore, the PBE is a pooling equilibrium in pure strategies with $\lambda = 1$.*
Proof. *See Appendix.* ■

Proposition 1.3 shows that, in the equilibrium all consumers have an incentive to anonymize, i.e. $\lambda = 1$. Consequently, firms resort to uniform pricing. Similar to the open data environment, this result is derived under pooling beliefs of firm A and B. In the proof of Proposition 1.3 we use the same refinement argument as before and find that there is no profitable individual deviation, when relaxing the pooling beliefs.

Same as in the analysis of the open data environment, we now turn to a situation where firms form separating beliefs, so that we can identify other potential equilibria. The results are summarized in the following Proposition.

Proposition 1.4 *There exists no separating equilibrium in pure strategies in the exclusive data environment. The pooling equilibrium derived above is unique among pure strategies.*
Proof. *See Appendix.* ■

Proposition 1.4 proves the uniqueness of the equilibrium under exclusive data, in which all the consumers hide their information. Combining Propositions 1.3 with 1.4, it follows that in the unique equilibrium firms set uniform prices. Thus, the exclusive data environment yields the same result as the benchmark case in Fudenberg and Tirole (2000), where price discrimination is either prohibited or first-period buying decisions are not observable.

While in the open data environment consumers increase competition between firms through their choice to reveal data, here consumers cannot influence competition between firms with their cookie choice. In the exclusive data environment, firms do not operate under symmetric information when consumers reveal their data. Therefore, by sharing cookies in this data environment consumers are worse off because firms can use the data to price discriminate on them without needing to intensify competition. In the exclusive data environment, firms obtain larger profits because they do not receive information about their consumers. Therefore, the firms cannot set customized prices but have to conform to a uniform pricing strategy.

1.2.3 Welfare

In this step, we analyze consumer and producer surplus as well as social welfare for both data environments. The theoretical analysis is based on the equilibria we find in Proposition 1.1 and Proposition 1.3.

The producer surplus (profit) shows that in equilibrium firms prefer a setting where information is not shared with a competitor as

$$\pi^*_{open} = \frac{17}{18}\bar{\theta}^2 < \pi^*_{excl.} = \bar{\theta}^2.$$

The profits are larger in the equilibrium under exclusive data. Consumers' equilibrium strategy is to anonymize, hence firms set uniform prices in both periods. Compared to the open data environment, prices are higher in the second stage of the exclusive data environment, benefiting firms. In the open data environment, profits are lower because in equilibrium consumers choose to accept cookies. This leads to an increase in competition among the two firms. In our model, firms cannot commit to not use information about their customers. Therefore, firms prefer a setting where in equilibrium they do not receive any information about consumers.

For consumers the case is not as simple, since they receive different utilities based on their type. Utilities are determined by the data environment and the buying decisions over two periods. It matters whether consumers are loyal to a firm over both periods or whether they were poached in the second period, i.e., they switch between firms. The type-dependent equilibrium utilities for the different data environments are given by the following terms:

$$U^*_{open}(\theta) = \begin{cases} 2(v - \bar{\theta} - \theta) & \text{for } \theta \in [0, \frac{\bar{\theta}}{3}) \\ 2v - \frac{8}{3}\bar{\theta} & \text{for } \theta \in (\frac{\bar{\theta}}{3}, \frac{2\bar{\theta}}{3}) \\ 2(v - 2\bar{\theta} + \theta) & \text{for } \theta \in (\frac{2\bar{\theta}}{3}, \bar{\theta}], \end{cases}$$

$$U^*_{excl.}(\theta) = \begin{cases} 2(v - \bar{\theta} - \theta) & \text{for } \theta \in [0, \frac{\bar{\theta}}{2}) \\ 2(v - 2\bar{\theta} + \theta) & \text{for } \theta \in (\frac{\bar{\theta}}{2}, \bar{\theta}]. \end{cases}$$

When comparing the utility levels of the different data environments, we find that consumers obtain the same utility for $\theta \in [0, \frac{\bar{\theta}}{3})$ and $\theta \in (\frac{2\bar{\theta}}{3}, \bar{\theta}]$, but obtain a higher utility for $\theta \in (\frac{\bar{\theta}}{3}, \frac{2\bar{\theta}}{3})$ from the open data environment. Consumers who are located further away from the firms can benefit from behavior-based pricing and receive a larger rent due to lower poaching prices that are available to them.

From the utilities we can derive the consumer surplus for both data environments as

$$CS_{open} = 2v\bar{\theta} - \frac{22}{9}\bar{\theta}^2, \qquad CS_{excl.} = 2v\bar{\theta} - \frac{5}{2}\bar{\theta}^2.$$

We find that

$$CS_{open} > CS_{excl}.$$

Consumers and firms prefer opposing data environments. Consumers' interest is to share their data with all firms on the market because firms cannot commit to not use the data. This increases competition between firms. On the other hand, firms benefit from a situation in which each competitor keeps their consumers' data to themselves. The level of data available to firms drives the results.

The total welfare for both data environments is

$$W_{open} = 2v\bar{\theta} - \frac{5}{9}\bar{\theta}^2, \qquad W_{excl.} = 2v\bar{\theta} - \frac{1}{2}\bar{\theta}^2.$$

From this follows

$$W_{excl.} > W_{open}.$$

The overall welfare level is higher under the firm-preferred, exclusive data environment. The efficiency loss incurred by firms in an open data environment is larger than the loss of consumers in an exclusive data environment. The welfare loss under open data comes from inefficient switching, i.e., consumers that are poached do not buy from the closest firm. While consumers gain from being poached, as can be seen in the comparison of their utility levels, firms lose profits (compared to the exclusive data environment) because of the lower poaching prices they set.

The theoretical analysis shows that social welfare is lower in the open data environment, since sharing of data between firms incentivizes consumers to grant access to their data and to inefficiently switch between firms.

1.3 Experiment

As we have shown, our theory makes strong predictions towards consumers' privacy choices. It suggests that an open data directive could benefit consumers, while probably doing so at cost of total welfare. However, this requires consumers to be fully rational by choosing to share their data with firms in an open data environment. Because consumers have an active role in the theoretical model it would be desirable to empirically verify their behavior and check the implications of our model. However, we cannot use real-world data because firstly, to our knowledge there is no mandated open data directive in place and secondly, we would need to gather data on consumers who may object to their data being gathered.

Due to these reasons, we employ a laboratory experiment. This circumvents the stated issues and allows us to *i)* fully control the data environment and *ii)* fully observe whether and which data are disclosed by consumers. Going into our experimental design, we derive qualitative hypotheses from our theoretical model.

1.3.1 Hypotheses

For our first hypothesis, we define *second-period discounts* as any difference between the first-period price and a second-period price (loyalty, poaching or new customer price). Comparing first- and second-period prices within data environments following Propositions 1.1 and 1.3 we arrive at Hypothesis 1.

Hypothesis 1 *We expect second-period discounts in the open data environment, but not in the exclusive data environment.*

We define *poaching discounts* as a (positive) difference between loyalty price and poaching price.[21] Note that firms cannot set poaching prices in the exclusive data

[21]Similarly, we define *loyalty discounts* as a (positive) difference between new customer price and loyalty price.

environment, but may "poach" by means of the new customer price. We only expect poaching discounts in the open data environment, because from the theoretical model, we learned that firms set lower poaching prices to induce customers who bought from their competitor to switch.

Hypothesis 2 *We expect poaching discounts in the open data environment but not in the exclusive data environment.*

From the theoretical analysis, we expect that all consumers reveal their information in the open data environment, while no consumer should reveal information in the exclusive data environment.[22] When all consumers disclose their information, both data environments conform to behavior-based price discrimination. The opposite case, i.e., full anonymization, corresponds to uniform pricing. While full disclosure is always better for consumers, the exclusive data environment yields a coordination problem for consumers, since every consumer has an incentive to anonymize.

Hypothesis 3 *We expect more information disclosure in the open data environment compared to the exclusive data environment.*

In the following, we define *switching* as any instance of consumers that purchase from a different firm in period two than in period one. Further, we define *poaching* as any instance of *switching* when consumers switch from their nearest firm to their respective farthest firm. This entails negative impacts on total welfare (cf. Section 1.2.3). Likewise, we define *retaining* as any instance of *switching* where consumers shift from the farthest to the nearest firm. This form of switching restores efficiency in terms of total welfare. Given that our derived equilibria are symmetric, we do not expect any instances of retaining, which implies that every occurrence of switching should follow our definition of poaching. In theory, we observed that welfare in the open data environment was lower than in the exclusive data environment because of poaching.

Hypothesis 4 *We expect more switching in the form poaching and lower total welfare in the open data environment compared to the exclusive data environment.*

1.3.2 Design

Our experimental design has two parts. The first and main part is a multi-stage market game, closely resembling our theoretical set-up. In the second part, we collect additional measures to control for cognitive ability, privacy concern and demographics.

[22] Due to discretization, consumers bear a mass in the experiment. However, no matter what the number of consumers is, at most one consumer who is located centrally would disclose information.

1.3.2.1 Market game

Our implemented market game closely follows the theoretical set-up and aims at testing our predictions concerning the buyers' privacy choices and the sellers' pricing choices under the two data environments. Subjects take the role of buyers or sellers, corresponding to consumers and firms in our theoretical model, with roles remaining fixed for the duration of the experiment. Each market contains six buyers and two sellers and lasts for two periods. A market is formed by eight adjacent locations, with sellers being located at either end and six buyers in between on distinct locations as depicted in Figure 1.5.

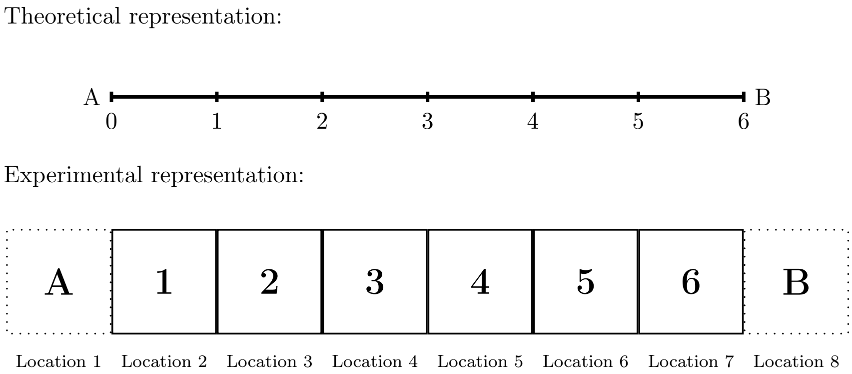


Figure 1.5: Conversion of theoretical into experimental market.

Two markets are simultaneously formed within one matching group, with matching groups consisting of six buyers and four sellers. Buyers are active in both markets with locations drawn independently. Sellers are only active in one market and are randomly located at location 1 or location 8, which corresponds to taking the role of seller A or seller B. This allows for a randomization of seller composition between market rounds, so that markets are independent between rounds and resemble one-shot interaction.[23] In total there are 20 market rounds to allow participants to get acquainted with the market game.

Similar to Camacho-Cuena et al. (2005) and Barreda-Tarrazona et al. (2011), we allow sellers to choose integer prices from the interval $[0, 10]$. Buyers exert unit transportation costs per unit of distance traveled.[24] Under consideration of transportation costs, the price interval ensures that buyers never have negative earnings. Our two treatment variations are (i) open data treatment and (ii) exclusive data treatment according to the two data environments in our theoretical model.

The course of action follows the timeline of the theoretical model. Initially, sellers choose the first-period price. Buyers afterwards decide whether to purchase from seller A or B and whether to allow tracking of their purchase decision or not. Sellers

[23] In comparable seller-only experiments by Brokesova et al. (2014), matching groups of four were shown to be suitable, according to Mahmood (2014) buyer involvement increases when active in multiple markets.

[24] For example, a buyer at location five has to bear transportation costs of five to buy from a seller at location zero.

then learn the first-period price of their competitor and the number of buyers of both sellers. They do not learn which or how many buyers allow tracking of their purchase. By this we employ a fully belief-based interpretation of our theoretical model, with beliefs not only governing the distribution, but also the share of anonymizing buyers. In the second period of the open data treatment, sellers choose a loyalty price, a poaching price and a new-customer price. In the second period of the exclusive data treatment, sellers are limited to choosing a loyalty price and a new customer price. After sellers have chosen the second-period prices, buyers are confronted with one price per seller according to their first-period purchase and tracking decisions as shown in Table 1.1.

Purchase decision	Tracking decision	Price of seller A	Price of seller B
Open data treatment			
Seller A	allow	Loyalty price	Poaching price
Seller A	don't allow	New customer price	New customer price
Seller B	allow	Poaching price	Loyalty price
Seller B	don't allow	New customer price	New customer price
Exclusive data treatment			
Seller A	allow	Loyalty price	New customer price
Seller A	don't allow	New customer price	New customer price
Seller B	allow	New customer price	Loyalty price
Seller B	don't allow	New customer price	New customer price

Table 1.1: Prices visible to buyers according to purchase and tracking decision.

Buyers then make their second-period purchase decision. After this, the sellers receive full information about the buyers' decisions. By this they also indirectly learn about the buyers' tracking decisions. This information is fully conclusive in case of the open data treatment, as the total number of buyers that bought at the loyalty or poaching prices corresponds to the total number of buyers that allow tracking. In the exclusive data treatment, it serves as a lower bound, in the number of buyers that bought at the loyalty prices. Those who bought at the new customer prices may or may not have allowed tracking. When entering a new market round, the information of all past market rounds is accessible via a history box. While market rounds are independent, the history of past rounds may serve sellers in forming their beliefs of the share of anonymous consumers.

At the end of a market round, a seller receives the profit

$$\Pi = p_1 \cdot n_1 + \mathbf{p_2} \cdot \mathbf{n_2'}$$

with p_1 corresponding to the chosen first-period price under which n_1 is the number of buyers who bought from the seller. Similarly, $\mathbf{p_2}$ is the vector of the second-period prices and $\mathbf{n_2}$ the vector of the number of second-period buyers who bought from the seller. Buyers have an induced reservation value of 15. The utility of a buyer for a purchase[25] is

$$U_t = 15 - p_t - \tau$$

with p_t describing the price of the product that the buyer chose in period t and τ describing the transportation costs. Profits and utilities are aggregated over all 20 market rounds, making every decision payment relevant.

1.3.2.2 Control measures

We complemented our market game by collecting several control measures. First, we employed a novel single-player version of the *Game of 21* Dufwenberg et al. (2010) which we call the *Game of 22*. This task serves several purposes. We suspect pricing decisions in this rather complex environment to be cognitively challenging for subjects. Heterogeneity of the subjects can lead to different observations of pricing behavior. We capture some of this heterogeneity in the capability of iterative reasoning. Likewise, buyers' first period purchasing and privacy choices may be correlated with their ability to backward induct. A full description, instructions and results of the Game of 22 are found in the Appendix.

Second, in an ensuing questionnaire, we ask participants to express their opinion about privacy issues and whether they are concerned about privacy breaches. The survey is based on Malhotra et al. (2004), which we use to calculate the *Internet Users' Information Privacy Concerns* (IUIPC) score. It consists of ten statements, to which participants answer on a seven-point Likert scale from "strongly agree" to "strongly disagree".[26] Agreeing to the statement reflects a higher "privacy concern". The statements cover three broad categories: data collection, data control and data usage. The IUIPC score is calculated as the equally weighted average of the average within-category scores normalized to $[0, 1]$. We use the score as a rough indication of the participants' general stance towards privacy related issues.

In the post-experimental questionnaire, we additionally collected the participants age, gender and field of study.

1.3.2.3 Procedure

In total 160 students participated, with 96 taking the role of a buyer and 64 taking the role of a seller in the market game. For both treatments, we formed eight independent matching groups with six buyers and four sellers each. Both buyers' utilities and sellers' profits from the market game are measured in *ECU* (Experimental Currency Unit) and exchanged at the rate 10 $ECU = 0,20$ EUR. On average, subjects earned about 20 EUR in the 90 minutes experiment. Most subjects were majors in economics, mathematics or industrial engineering. 36 % of the subjects were female. Participants earned 2 EUR when they won against the computer in the Game of 22, which 91.25 %

[25] Within one market round a buyer makes four purchases. One per period per market.
[26] The full questionnaire is found in the Appendix.

of the participants successfully did. Lastly, participants were awarded 1 EUR for filling out the privacy survey. Sessions were conducted in the laboratory of TU Berlin and WZB in September and November 2019 with participants drawn from the ORSEE pool (Greiner, 2015). The experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007).

1.3.3 Results

Seller and buyer decisions are mutually dependent. Therefore, we first briefly discuss summary statistics concerning both buyers and sellers. Afterwards, in order of action, we examine sellers pricing decisions and then buyers purchasing and privacy decisions, including switching patterns and welfare implications.[27]

Treatment	Open data	Exclusive data
First-period price		
All 20 rounds	5.68	5.47
Last 10 rounds	5.55	5.54
Equilibrium prediction	8	6
Loyalty price		
All 20 rounds	4.12	3.94
Last 10 rounds	3.97	4.07
Equilibrium prediction	4	n/a
New customer price		
All 20 rounds	4.20	4.02
Last 10 rounds	3.85	3.79
Equilibrium prediction	n/a	6
Poaching price		
All 20 rounds	3.28	n/a
Last 10 rounds	3.01	n/a
Equilibrium prediction	2	n/a

Table 1.2: Summary statistics for pricing choices of sellers.

Table 1.2 shows average prices of all 20 rounds and the last ten rounds of the experiment and the associated theoretical predictions. The inclusion of separate statistics for the second half of the experiment accounts for learning and the continuing formation of beliefs. First-period prices are substantially larger than second-period prices in both treatments and overall somewhat higher in the open data treatment compared to the exclusive data treatment. In the open data treatment, we observe poaching prices about one unit below loyalty and new customer prices, while the latter two are relatively equal. This difference remains constant, while overall prices are lower in the second half. In the exclusive data treatment, we observe some poaching by means of the new customer prices, which are below loyalty prices in the second half of the experiment.

[27]While buyers actions dictate sellers beliefs, we assume those to be fixed when entering a new market round. Likewise, buyers beliefs about second period prices are fixed when entering a new market round.

Treatment	Open data	Exclusive data
Information disclosure		
All 20 rounds	67.19 %	65.36 %
Last 10 rounds	66.77 %	58.54 %
Model prediction	100 %	0 %
Share of switching		
All 20 rounds	23.18 %	15.73 %
Last 10 rounds	23.44 %	17.40 %
Model prediction	$33.\bar{3}$ %	0 %
Share of poaching		
All 20 rounds	13.02 %	7.50 %
Last 10 rounds	13.02 %	9.17 %
Model prediction	$33.\bar{3}$ %	0 %
Share of retaining		
All 20 rounds	10.16 %	8.23 %
Last 10 rounds	10.42 %	8.23 %
Model prediction	0 %	0 %

Table 1.3: Summary statistics for purchasing and privacy choices of buyers.

We find buyers do not favor one seller over the other. In the open data treatment (exclusive data treatment), 49.01 % (51.25 %) purchased from seller A in the first period and 49.69 % (49.48 %) purchased from seller A in the second period.[28] Buyers rather predominantly purchase at the lowest total costs, where total costs are the sum of the price and transportation costs. In the open data treatment (exclusive data treatment), 97.29 % (96.56 %) of the first-period purchases and 97.34 % (98.39 %) of the second-period purchases were made at the lowest total costs.[29] As shown in Table 1.3, the share of information disclosure is nearly equal for both treatments at around $\frac{2}{3}$. We find that the rate decreases for the second half in the exclusive data treatment. Switching is more prevalent in the open data treatment compared to the exclusive data treatment. However, we observe an increase in switching over time in the exclusive data treatment which is driven by an increase in poaching, as the share of retaining remains unaffected.

Going forward, we express purchases in terms of the proximity to the closest seller to account for the symmetry of the market environment. This allows us to clearly distinguish *switchers* into two subgroups as defined for Hypothesis 4. We consider those as *poached* who first purchase from their close seller and switch to their far seller and those as *retained* who first purchase from their far seller and switch to their close seller. While the former is detrimental to total welfare, the latter restores welfare in inefficient first-period outcomes. In Table 1.3, we show that there is considerable *retaining* in both treatments.

In Table 1.B.1, we show the order of purchases per buyer location. We observe that the share of those who bought from the same seller twice decreases with increasing

[28]When restricting to the last ten rounds all figures are closer to 50 %

[29]When restricting to the last ten rounds all figures are closer to 100 %.

distance from the seller. Switchers who purchased from different sellers between periods are more prevalent closer to the center, with highest occurrence at the central locations 4 and 5. Further, we show the distribution of information disclosure in Table 1.B.1. At first glance we find that information disclosure is largely independent of locations in both treatments. Notably disclosure rates are slightly smaller (larger) in the central locations in the open data treatment (exclusive data treatment). However, Pearson's chi-squared tests neither reveal a significant difference from a uniform distribution in the open data treatment, $\chi^2(5, N = 1290) = 3.78, p = 0.58$, nor in the exclusive data treatment, $\chi^2(5, N = 1255) = 2.57, p = 0.77$.[30]

1.3.3.1 Sellers' pricing decisions

First we investigate price setting of sellers within treatments as this is instrumental to understand privacy and purchasing decisions of buyers. We employ a fixed-effects regression, clustered on group level. We regress on respective price differences and analyze the constant remainder, while considering the impact of learning, since the fixed-effects absorb any other subject-specific characteristics.

As shown in Table 1.4, we find significant differences between all second-period prices compared to first-period prices. We expected this for the open data treatment, but not for the exclusive data treatment according to Hypothesis 1. Predictions for the exclusive data treatment are rested on the fact that consumers fully anonymize. However, we observe a high rate of information sharing, which is consistent with differences between first- and second-period prices. As a second-order effect this should also lead to price discrimination, which we only observe to a small extent in the second half as seen in the last column of Table 1.4.

There are significant differences between poaching price compared to loyalty and new customer price in the open data treatment. These differences remain over the course of the experiment. We find mixed results on the difference between new customer and loyalty prices. Initially, new customer prices are significantly larger than loyalty prices, while the opposite is true in the second half of the experiment as indicated by the second-half dummy for both treatments. However, this is only significant in the exclusive data treatment and it is the only instance of a significant impact of the second-half dummy that is reversed to the initial effect.

Now we turn to the relation of information disclosure and pricing strategies. Especially in the exclusive data treatment the high rate of information sharing should have led sellers to increase their loyalty prices according to our theory. Sellers initially seem reluctant to do so, but we find some indication of sellers adopting poaching strategies in the exclusive data treatment towards the end of the experiment. Furthermore, the analysis of pricing behavior of sellers sheds some light on the high rate of information disclosure in the early rounds of the exclusive data treatment,

[30] In Section 1.B in the Appendix we explore how privacy concern affects disclosure rates for some locations.

	p_{intro} $-p_{new}$	p_{intro} $-p_{loyal}$	p_{intro} $-p_{poach}$	p_{new} $-p_{loyal}$	p_{new} $-p_{poach}$	p_{loyal} $-p_{poach}$	p_{intro} $-p_{new}$	p_{intro} $-p_{loyal}$	p_{new} $-p_{loyal}$
Constant	1.266***	1.500***	2.247***	0.234*	0.981***	0.747***	1.144***	1.538***	0.394*
	(0.113)	(0.097)	(0.064)	(0.119)	(0.124)	(0.088)	(0.136)	(0.071)	(0.167)
Second half	0.434*	0.116	0.300*	-0.319	-0.134	0.184	0.616*	-0.062	-0.678*
	(0.226)	(0.195)	(0.129)	(0.237)	(0.248)	(0.176)	(0.273)	(0.143)	(0.334)
Treatment	Open data			Open data			Exclusive data		
Subjects	32	32	32	32	32	32	32	32	32
Observations	640	640	640	640	640	640	640	640	640

p_{intro} – First-period price, p_{loyal} – loyalty price, p_{new} – New customer price, p_{poach} – Poaching price. Standard errors in parentheses. Estimation by fixed-effects regression with clustering on group level. *, ** and *** denote significance at the 10 %, 5 % and 1 % level, respectively.

Table 1.4: Fixed-effects regression on price differences within treatments.

as sellers in fact offer loyalty discounts in the early rounds and only later adopt a different strategy, where they actually employ loyalty mark-ups.

Lastly, we are interested in differences in price setting behavior between treatments. We measure the effects on prices between treatments by random-effects regressions with group-level clustering. Since fixed-effects regression is not applicable to detect treatment differences, we use available controls in demographics, iterative thinking capability and learning effects.

In Table 1.5, we show the results. We find no significant effects on first-period, loyalty and new customer prices. Though insignificant, the signs of all three effects correspond to our theoretical predictions. Most notably there is a significant effect on poaching prices, indicating that sellers poach more (intensively) in the open data treatment, by roughly the same magnitude as the within-treatment analysis has revealed for the open data treatment. These results are in favor of Hypothesis 2.

We calculate the optimal average second-period prices under the observed share of anonymous consumers and the observed number of first-period buyers according to our derived reaction functions from Lemmas 1.1 and 1.2 to correct the predictions of our model for the respective second-period sub-game under pooling beliefs. We have shown earlier via chi-squared tests that the privacy choices over locations are not significantly different from a uniform distribution, supporting the use of pooling beliefs here.

In Table 1.6, we show the observed prices compared to the predictions when adjusted for the observed first-period purchasing and privacy choices. In Figure 1.B.6 and Figure 1.B.7, we show how the observed and predicted prices develop over rounds. We find that sellers adjusted loyalty and poaching prices in the open data treatment reasonably well. We find a striking discrepancy for the new customer price in the open data treatment compared to the prediction. As we have shown in Table 1.4, sellers chose new customer prices relatively close to loyalty prices. This is reminiscent of the off-path response of sellers to deviating buyers, which we lay out in Lemma 1.A.1. While this should lead to a ratchet effect on the loyalty and poaching prices, which we do not observe, it might explain the sellers approach. In the exclusive data treatment, we see a similar but slowed down adjustment process to the open data treatment for loyalty and poaching prices. Together with the second-period discounts, this qualitatively fits the predictions from our model when accounting for observed first-period purchases and privacy choices.

1.3.3.2 Buyers' purchasing and privacy choices

Though buyers opted for the lowest total costs when purchasing, this does not conclusively suggest myopic purchasing decisions. To account for strategic purchase decisions, we check what purchasing decisions buyers made when total costs were equal.

	First-period price		New customer price		Loyalty price		Poaching price	
Exclusive	-0.205	-0.021	-0.173	0.167	-0.153	0.162	0.741*	0.920*
	(0.442)	(0.395)	(0.503)	(0.444)	(0.423)	(0.345)	(0.446)	(0.499)
Learning	No	Yes	No	Yes	No	Yes	No	Yes
Demographics	No	Yes	No	Yes	No	Yes	No	Yes
Iterative thinking	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1280	1280	1280	1280	1280	1280	1280	1280

We use *poaching price* ≡ *new customer price* in the exclusive data treatment. Standard errors in parentheses. Estimation by random-effects regression with clustering on group level. *, ** and *** denote significance at the 10 %, 5 % and 1 % level, respectively.

Table 1.5: Random-effects regression on treatment effects for prices.

	Loyalty price	New customer price	Poaching price
Open data treatment			
Observed average prices			
All 20 rounds	4.20	4.12	3.28
Last 10 rounds	3.85	3.94	3.01
Model prediction			
All 20 rounds	4.12	6	2.14
Last 10 rounds	4.13	6	2.11
Exclusive data treatment			
Observed average prices			
All 20 rounds	3.94	4.02	n/a
Last 10 rounds	4.07	3.79	n/a
Model prediction			
All 20 rounds	4.55	3.10	n/a
Last 10 rounds	4.66	3.33	n/a

Table 1.6: Observed and adjusted price predictions under pooling assumption.

Open data treatment	Tracking allow	Tracking don't allow
First half	59.57 %	43.48 %
Second half	70.83 %	55.17 %

Exclusive data treatment	Tracking allow	Tracking don't allow
First half	36.84 %	35.29 %
Second half	35.59 %	33.33 %

Table 1.7: Share of purchases from the far seller at equal total costs.

As shown in Table 1.7, the share of buyers who purchase at the far seller when total costs are equal increases towards the second half of the experiment and is amplified for those who allow purchase tracking in the open data treatment. The same is not true for the exclusive data treatment, where the share is within two percentage points around 35 % under all conditions. As sellers offered loyalty discounts in the initial rounds, it is sensible for buyers to stick with the close seller initially. Though sellers refrained from offering loyalty discounts in the later rounds, buyers did not adapt and were still more likely to choose the close seller when total costs were equal. In Table 1.B.2 in the Appendix, we show that we can confirm a significant treatment effect. Under equal total costs buyers were more likely to purchase from the far seller in the open data treatment, suggesting strategic purchase decisions in the first period.

Upon first inspection in Figure 1.6, we observe two things regarding the purchase tracking decision between treatments over rounds. Allowing tracking is initially more and subsequently less prevalent in the exclusive data treatment compared to the open data treatment. Albeit the similar sharing rate over all treatments, this suggests that the adaptive processes are different between treatments. This reflects the findings of Schudy and Utikal (2017) who show that subjects are less inclined to share information, if more parties receive the information. Subjects in our experiment face a similar situation, since there are two recipients in the open data treatment and only one in the exclusive data treatment.

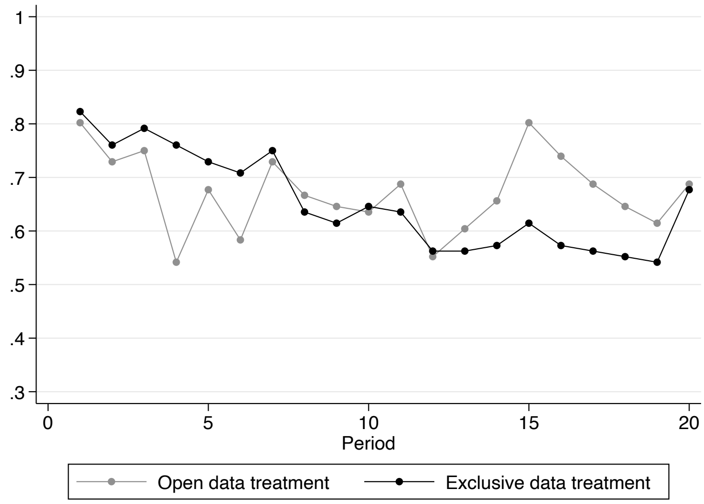


Figure 1.6: Share of purchase tracking allowed over periods by treatment.

	Dependent variable: Tracking allowed $\in \{0, 1\}$			
	Treatment		Treatment + Learning	
	(1)	(2)	(3)	(4)
Exclusive	0.036	0.357	0.442	0.777
	(0.278)	(0.501)	(0.295)	(0.516)
Second half			-0.046	-0.046
			(0.107)	(0.107)
Exclusive × Second half			-0.763***	-0.771***
			(0.156)	(0.157)
Market	No	Yes	No	Yes
Location	No	Yes	No	Yes
Demographics	No	Yes	No	Yes
Privacy concern	No	Yes	No	Yes
Iterative thinking	No	Yes	No	Yes
Observations	3840	3800	3840	3800

Standard errors in parentheses. Estimation by multilevel mixed-effects logistic regression with hierarchical clustering on group and subject level. *, ** and *** denote significance at the 10 %, 5 % and 1 % level, respectively.

Table 1.8: Impact of learning on tracking decision.

In Table 1.8, we explore this by employing a multi-level logit model on the tracking decision of buyers, while controlling for demographics and experiment specific factors, as well as, iterative thinking capability and privacy concern. Following specifications (1) and (2), we see no immediate treatment effect. In specifications (3) and (4), we explore the role of learning, by including a dummy variable which indicates the second half of the experiment, corresponding to rounds 11 and after, and an interaction effect of treatment and second half dummy.[31] There is a significant drop in information disclosure in the exclusive data treatment, while there is no change after learning in the open data treatment. We find some evidence towards Hypothesis 3, when accounting for learning effects. We observe less information sharing in the exclusive data treatment over time, though information sharing is much more prevalent than predicted. This reflects the public good nature of information disclosure in the data environment.

	Dependent variable:					
	Switched $\in \{0,1\}$		Poached $\in \{0,1\}$		Retained $\in \{0,1\}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Exclusive	-0.501***	-0.065	-0.658***	-0.111	-0.223	-0.064
	(0.148)	(0.198)	(0.226)	(0.325)	(0.147)	(0.225)
Tracking		0.600***		0.649***		0.247
		(0.140)		(0.174)		(0.177)
Exclusive × Tracking		-0.597***		-0.677**		-0.203
		(0.208)		(0.271)		(0.263)
Market	No	Yes	No	Yes	No	Yes
Location	No	Yes	No	Yes	No	Yes
Demographics	No	Yes	No	Yes	No	Yes
Privacy concern	No	Yes	No	Yes	No	Yes
Iterative thinking	No	Yes	No	Yes	No	Yes
Observations	3840	3840	3840	3800	3840	3840

Standard errors in parentheses. Estimation by multilevel mixed-effects logistic regression with hierarchical clustering on group and subject level. *, ** and *** denote significance at the 10 %, 5 % and 1 % level, respectively.

Table 1.9: Effects of treatment and privacy choice on switching, poaching and retaining of buyers.

Next, we take a closer look at the switching behavior of buyers. As discussed earlier and shown in Table 1.B.1, we observe instances of *poached* and *retained* buyers. In specification (1) of Table 1.9, we show that switching is significantly more prevalent in the open data treatment. In specification (2), we show that this effect is not merely driven by the treatment, but by those who disclose information. While the effect is significant and positive in the open data treatment, we find a negative significant effect with nearly the same magnitude in the interaction with the exclusive data treatment. This indicates that information disclosure is predictive of switching in the open data treatment, but not in the exclusive data treatment. We observe the same pattern in specifications (3) and (4) when limiting to those instances of *switching* that follow our definition of *poaching.* In contrast, none of the stated effects is found when limiting to *retained* buyers in specifications (5) and (6), suggesting that this is neither driven by the treatment, nor by the privacy decisions. Together, the results speak in favor of the first part of Hypothesis 4. We observe significantly more switching, in the form of poaching, in the open data treatment compared to the exclusive data treatment.

[31] Results are similar when using a continuous variable indicating the round instead of the dummy for the second half.

1.3.3.3 Welfare findings

In order to analyze the effect of switching on welfare, we use average transportation costs as an inverse measure for welfare. Figure 1.7 depicts predicted and observed average transportation costs. The left and right boundaries of the line give the

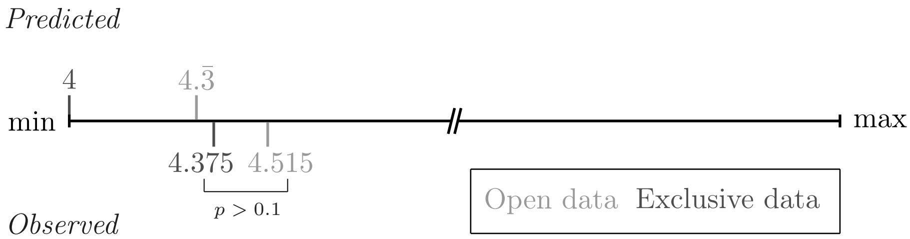


Figure 1.7: Observed and predicted average transportation costs per round.

average minimal and maximal transportation costs per market round (i.e., two periods). This implies that the left boundary corresponds to the maximum welfare. Four are the lowest average transportation costs per round if buyers purchase from the closest seller. This is also the predicted value for average transportation costs in the exclusive data treatment because we expect all buyers to anonymize and buy from the closest seller in both periods. The predicted average transportation costs for the open data treatment are $4.\bar{3}$ because we expect all buyers to share information and a portion of 1/3 to switch (cf. Table 1.3) to the far seller in the second period. Underneath the line, we depict the observed average transportation costs across treatments. The exclusive data treatment's observed average transportation costs are 4.375. The open data treatment's observed average transportation costs are 4.515. Although both values are close to the maximum welfare of four, they are above the prediction of the open data treatment of $4.\bar{3}$. Based on a random effects regression clustered on group level with time fixed effects, we do not find a significant difference between the observed transportation costs across treatments. This means that social welfare is not significantly different between the open and exclusive data treatment, despite higher switching rates in the open data treatment. This relies on the fact that switching not only occurs inefficiently due to poaching of customers, but also efficiently in retaining close customers. We cannot confirm the second part of Hypothesis 4.

1.4 Conclusion and Discussion

In this chapter, we analyze consumers' endogenous privacy decisions in a duopolistic, dynamic market where firms employ behavior-based price discrimination. We consider two data environments, distinct in their data sharing levels. Data are contained in cookies placed by firms and reveal consumers' purchasing history. In the open data environment, data disclosed by consumers are fully shared between firms, whereas in the exclusive data environment data are only available to the provider of the good.

In our theoretical analysis, we find a unique pure-strategy equilibrium for each data environment. When information is available to both firms, all consumers fully disclose their data, which amplifies competition. Second-period prices are below first-period prices and firms offer poaching discounts. When information is exclusive to firms, all consumers hide their data because they are individually better off by anonymizing. Second-period prices and first-period prices correspond to uniform pricing. While consumers' data sharing is favorable in both data environments, there is an incentive to do so in the open data environment, but not in the exclusive data environment. The exclusive data environment exhibits information externalities where a collective choice of full information disclosure would lead to a better outcome for consumers, but individually consumers refrain from sharing information. This is also reflected in consumer's welfare which suffers under exclusive data and is higher under open data due to poaching discounts. For firms, profits are higher in the exclusive data environment. Social welfare is maximal in the exclusive data environment because in the absence of poaching discounts there is no inefficient switching.

In order to verify our theoretical results, we conduct a laboratory experiment that is aligned with our theoretical model with subjects acting in the roles of sellers and buyers. We employ two treatments corresponding to the two data environments. We find that the data sharing rate in the open data environment is high which is in line with our theory. The data sharing rate in the exclusive treatment is significantly lower compared to the rate in the open data treatment when factoring in an adjustment process. Sellers act largely in accordance with our theory in the open data treatment. They price discriminate on the basis of data they receive by offering poaching discounts. In the exclusive data treatment, sellers initially do not offer discounts to anonymous buyers even though they have access to necessary information. Over time, sellers in the exclusive treatment begin to adopt poaching strategies and in turn buyers refrain from disclosing information, which is in line with our predictions.

The theoretical welfare results hinge on the unique pooling equilibria. That social welfare is higher under exclusive data is solely driven by the fact that there is no inefficient switching. However, we cannot confirm this social welfare effect in our experiment. Though we can confirm increased switching in the open data treatment over the exclusive data treatment, we find no significant difference in social welfare across treatments. From a policy maker's perspective, these are important results for the discussion on whether to implement an open data environment. The European Commission is already discussing such a mandated data sharing policy when consumers are in control over their own data (European Commission, 2020). In our analyses, the difference between open data and exclusive data environment shows that mandated data sharing among firms will lead more consumers to share data because they can benefit from intensified competition. Whereas under exclusive data, firms can use consumers' data to price discriminate without the pressure of increased competition because firms operate under asymmetric information.

It would be interesting to study consumers' concern for their data privacy in the e-commerce setting. When do consumers decide to share data? On what basis do consumers make their decision about accepting access to their cookies? When we think of extending our model, a setting in which consumers are in complete control of their data deserves attention. Complete control entails that consumers can decide whether each firm independently receives data about their previous purchases. This way, consumers can also exclusively share their purchasing history with firms that they have not bought from. Basically, this extends our open data environment by allowing consumers to choose a different option for each firm. Along this line, one can also imagine a situation of asymmetric information, i.e., a small retailer unable to collect and process consumers' data versus a large retailer accessing a wide range of personal data. It might be interesting to verify what firms' and consumers' optimal strategies are when one competitor is not able to use data.

It is equally important to explore firms' perspective and study under which conditions they have an incentive to share obtained data with other firms, as our open data environment implies mandated data sharing, while under exclusive data this possibility was not given at all. Another vein for future research is the extension of the time horizon to more than two periods, either with long-lived consumers or in form of a overlapping generations model.

1.A Appendix A: Theory

Proof of Lemma 1.1

Firms' maximization problems for anonymous consumers give the following first-order conditions

$$\frac{\bar{\theta}}{2} + \frac{p_2^B}{2} - p_2^A = 0 \qquad \frac{\bar{\theta}}{2} - p_2^B + \frac{p_2^A}{2} = 0.$$

From these we derive prices $p_2^A = p_2^B = \bar{\theta}$ and the marginal consumer, $\theta_2 = \frac{\bar{\theta}}{2}$.

By plugging $\theta_2^A = \frac{\bar{\theta}}{2} + \frac{p_{2,A}^B - p_{2,A}^A}{2}$ and $\theta_2^B = \frac{\bar{\theta}}{2} + \frac{p_{2,B}^B - p_{2,B}^A}{2}$ into the maximization problems, we have

$$\max_{p_{2,A}^A, p_{2,B}^A} \quad (1-\lambda)[p_{2,A}^A(\frac{\bar{\theta}}{2} + \frac{p_{2,A}^B - p_{2,A}^A}{2}) + p_{2,B}^A(\frac{\bar{\theta}}{2} + \frac{p_{2,B}^B - p_{2,B}^A}{2} - \theta_1)],$$

$$\max_{p_{2,B}^B, p_{2,A}^B} \quad (1-\lambda)[p_{2,B}^B(\bar{\theta} - \frac{\bar{\theta}}{2} - \frac{p_{2,B}^B - p_{2,B}^A}{2}) + p_{2,A}^B(\theta_1 - \frac{\bar{\theta}}{2} - \frac{p_{2,A}^B - p_{2,A}^A}{2})].$$

First-order conditions solve

$$(1-\lambda)[\frac{\bar{\theta}}{2} + \frac{p_{2,A}^B}{2} - p_{2,A}^A] = 0,$$

$$(1-\lambda)[\frac{\bar{\theta}}{2} + \frac{p_{2,B}^B}{2} - p_{2,B}^A - \theta_1] = 0,$$

$$(1-\lambda)[\frac{\bar{\theta}}{2} - p_{2,B}^B + \frac{p_{2,B}^A}{2}] = 0,$$

$$(1-\lambda)[\theta_1 - \frac{\bar{\theta}}{2} - p_{2,A}^B + \frac{p_{2,A}^A}{2}] = 0,$$

where we can derive the results as

$$p_2^A = \bar{\theta}, \qquad p_{2,A}^A = \frac{1}{3}(2\theta_1 + \bar{\theta}), \qquad p_{2,B}^A = \frac{1}{3}(3\bar{\theta} - 4\theta_1),$$

$$p_2^B = \bar{\theta}, \qquad p_{2,B}^B = \frac{1}{3}(3\bar{\theta} - 2\theta_1), \qquad p_{2,A}^B = \frac{1}{3}(4\theta_1 - \bar{\theta}).$$

From these equations we observe that anonymous prices p_2^A and p_2^B are strictly positive, the same for loyalty prices $p_{2,A}^A$ and $p_{2,B}^B$. However, poaching prices $p_{2,B}^A$ and $p_{2,A}^B$ depend on θ_1 and the parameter $\bar{\theta}$. When $\frac{1}{4}\bar{\theta} \leq \theta_1 \leq \frac{3}{4}\bar{\theta}$, it is an interior solution and the equilibrium prices are just as above. When $\theta_1 < \frac{1}{4}\bar{\theta}$, it is a corner solution where $p_{2,A}^B = 0$. Firm A should set $p_{2,A}^A$ such that $v - p_{2,A}^A - \theta_1 = v - (\bar{\theta} - \theta_1)$, in order to protect the marginal customer located at θ_1. Therefore $p_{2,A}^A = \bar{\theta} - 2\theta_1$ and the other pirces are the same as in the interior solution. When $\theta_1 > \frac{3}{4}\bar{\theta}$ it follows that $p^A_{2,B} = 0$, and thereby firm B sets $p^B_{2,B}$ such that $v - \theta_1 = v - p^B_{2,B} - (\bar{\theta} - \theta_1)$. So in this case $p^B_{2,B} = 2\theta_1 - \bar{\theta}$ and the other prices do not change.

Proof of Proposition 1.1

By inserting $p^A_{2,A}$, $p^B_{2,A}$, $p^A_{2,B}$, $p^B_{2,B}$, and θ_1 into firms' maximization problems in the first period, we can derive the fiirst-order conditions for A and B, respectively,

$$\frac{\bar{\theta}}{2} + \frac{3+\lambda}{8}p^B_1 - \frac{3+\lambda}{4}p^A_1 - \frac{5}{16}(1-\lambda)(p^B_1 - p^A_1) = 0,$$

$$\frac{\bar{\theta}}{2} + \frac{3+\lambda}{8}p^A_1 - \frac{3+\lambda}{4}p^B_1 + \frac{5}{16}(1-\lambda)(p^B_1 - p^A_1) = 0,$$

which gives us firms' prices for both periods.

When all consumers reveal their information, beliefs about anonymous consumers govern off-path behavior. If a single consumer individually deviates, both firms are driven to a situation of perfect competition for this single consumer, which grants the highest rent possible. Considering that both firms perfectly compete and denote $\tilde{u}(\theta)$ as the utility of a consumer of type θ who deviates:

$$\tilde{u}(\theta)^{32} = \begin{cases} v - \bar{\theta} + \theta & \text{if} \quad \theta \leq \dfrac{\bar{\theta}}{2} \\ v - \theta & \text{if} \quad \theta \geq \dfrac{\bar{\theta}}{2}. \end{cases}$$

From firms' perspective, their belief about who may deviate depends on the utilities a consumer gets with and without deviation. Based on the optimal pricing strategy from Proposition 1.1 and the utility with deviation $\tilde{u}(\theta)$ derived above, we check six cases separately: when $0 \leq \theta \leq \frac{\bar{\theta}}{6}$, the utility of a consumer of type θ without deviation is $v - \frac{2}{3}\bar{\theta} - \theta$, which is larger or equal to the utility $\tilde{u}(\theta)$ if they deviate, that is $v - \bar{\theta} + \theta$. When $\frac{\bar{\theta}}{6} < \theta \leq \frac{\bar{\theta}}{3}$, the utility of a consumer of type θ without deviation is again $v - \frac{2}{3}\bar{\theta} - \theta$, which is strictly smaller than the utility if they deviate, that is $v - \bar{\theta} + \theta$. When $\frac{\bar{\theta}}{3} < \theta \leq \frac{\bar{\theta}}{2}$, the utility of a consumer of type θ without deviation becomes $v - \frac{1}{3}\bar{\theta} - (\bar{\theta} - \theta)$, which is smaller than the utility $\tilde{u}(\theta)$ if they deviate, that is $v - \bar{\theta} + \theta$. Similarly, when $\frac{\bar{\theta}}{2} < \theta \leq \frac{2}{3}\bar{\theta}$, the utility of a consumer without deviation changes to $v - \frac{1}{3}\bar{\theta} - \theta$, which is smaller than the utility with deviation, equivalent to $v - \theta$. When $\frac{2}{3}\bar{\theta} < \theta < \frac{5}{6}\bar{\theta}$, the utility of a consumer without deviation is $v - \frac{2}{3}\bar{\theta} - (\bar{\theta} - \theta)$, which is smaller than the utility with deviation $v - \theta$. Finally, when $\frac{5}{6}\bar{\theta} \leq \theta \leq \bar{\theta}$, the utility of a consumer without deviation is again $v - \frac{2}{3}\bar{\theta} - (\bar{\theta} - \theta)$, which is larger or equal to the utility with deviation $v - \theta$. Overall, we get that consumers located between $\frac{1}{6}\bar{\theta}$ and $\frac{5}{6}\bar{\theta}$ may have an incentive to deviate, thus firms form their off-path belief accordingly. Figure 1.A.1 depicts the total costs $v - \tilde{u}(\theta)$

[32] In the perfect competition, the firm further away from the deviating consumer would set the price at zero and this consumer would be indifferent between buying from either firm.

for consumers under individual deviation, given the sellers' responses.

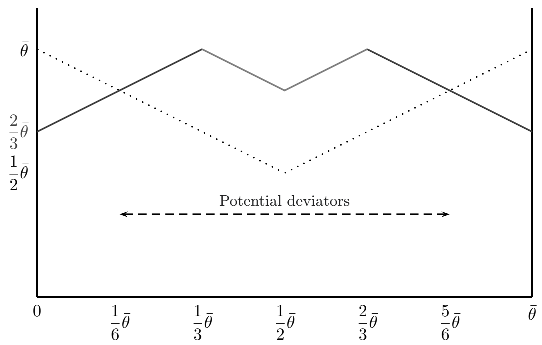


Figure 1.A.1: Total costs in equilibrium (solid) and for individual deviators (dotted).

Corollary 1.A.1 *If firms observe a deviation of consumers' privacy choice, they believe with equal probability that it is any consumer located at* $\theta \in (\frac{1}{6}\bar{\theta}, \frac{5}{6}\bar{\theta})$. *The off-path price for this segment is* $\frac{2}{3}\bar{\theta}$.

Since they cannot identify the exact type of the consumer who deviates, their belief is that the consumer with an incentive to deviate is uniformly distributed between $\frac{1}{6}\bar{\theta}$ and $\frac{5}{6}\bar{\theta}$. Therefore, as a best response, they set the optimal off-path price $\frac{2}{3}\bar{\theta}$ [33] if they observe a deviation. This price is equivalent to the optimal loyalty price derived in Proposition 1.1. Under these beliefs no consumer anonymizes because the total costs are not lower than under revealing information. Therefore, there is no profitable deviation for any consumer, which completes the proof.

Proof of Proposition 1.2

In this section, we prove the non-existence of a separating equilibrium in pure strategies under open data and thereby confirm the uniqueness of the pooling equilibrium derived in Proposition 1.2.

We divide all the potential scenarios into two cases: (i) when the first-period cut-off goes through a "hide" segment[34] and (ii) when the first-period cut-off goes through a "give" segment.[35] We differentiate separating equilibria according to whether the line consists of two segments or of mutiple segments. For instance, the Figure 1.A.2 shows the scenario of multiple segments when the first-period cut-off goes through a "hide" segment.

Definition: If not all consumers within one segment buy from the same firm, we say that there exists poaching behavior in this segment.

[33] Considering this off-path price, two firms face a continuum of consumers uniformly distributed between $\frac{1}{6}\bar{\theta}$ and $\frac{5}{6}\bar{\theta}$, thus they choose $\tilde{p}_2^A$ and $\tilde{p}_2^B$ to maximize their respective profits $\tilde{p}_2^A(\frac{\bar{\theta}}{2}+\frac{\tilde{p}_2^B-\tilde{p}_2^A}{2}-\frac{\bar{\theta}}{6})$ and $\tilde{p}_2^B[\frac{5}{6}\bar{\theta}-(\frac{\bar{\theta}}{2}+\frac{\tilde{p}_2^B-\tilde{p}_2^A}{2})]$, where we get that $\tilde{p}_2^A=\tilde{p}_2^B=\frac{2}{3}\bar{\theta}$.

[34] That is, to the left of the cut-off all the consumers bought from firm A in the first period and to the right all bought from firm B.

[35] Please note that no assumption about symmetry is needed.

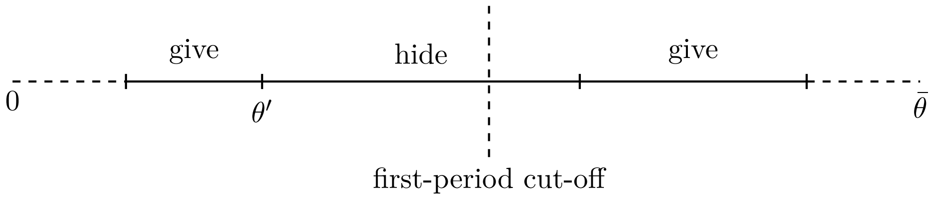


Figure 1.A.2: Line with multiple segments in case (i).

Lemma 1.A.1 *In a separating equilibrium with multiple segments, there exists no poaching behavior in any segment except for the segment that the first-period cut-off goes through, i.e., there is no poaching behavior in a lateral segment.*

Proof. We take the figure above as an example and use a proof by contradiction here. Assume Lemma 1.A.1 is not true and there exists poaching behavior in the left "give" segment, which means that to the left of θ' consumers buy from firm B at $p^B_{2,A}$ and to the right of θ' consumers buy from firm A at p^A_2. Since the consumer located at θ' is indifferent between revealing and hiding information, the costs of two options should be the same for them, i.e., $p^B_{2,A} + (\bar{\theta} - \theta') = p^A_2 + \theta'$. However, for those who are located to the left of θ' and buy from firm B at $p^B_{2,A}$, they have an incentive to deviate. That is, because by deviating to decline cookies, the total cost of buying from firm A would be strictly smaller than the cost before.[36] Thus, there exists a profitable deviation, which contradicts our initial assumption. The same method can be applied to a "hide" segment. This completes the proof. ■

Lemma 1.A.1 shows that in a separating equilibrium with multiple segments there is no poaching behavior in lateral segments. Based on cut-offs between the lateral segments we can infer that $p^i_2 = p^i_{2,i}\ \forall\ i = A, B$. Now, we start to prove the non-existence of a separating equilibrium in pure strategies.

As mentioned before, we have to look at case (i) and (ii) and in each case differentiate by the number of segments (two or multiple). In other words, we need to check four possible scenarios. Let's first focus on the figure above, where there are multiple segments in case (i). If we check the consumer located at θ', they are indifferent between revealing and hiding information. By Lemma 1.A.1, there is no poaching behavior in the "give" segments, so $p^A_{2,A} = p^A_2$. Similarly, $p^B_{2,B} = p^B_2$ also holds. However, under such circumstances both firm A and firm B have an incentive to deviate from their pricing strategy. By increasing their loyalty prices when the consumers are segmented as in the figure above, both firms could gain profit from loyal customers while keeping the profit from anonymous customers the same as before. Thus, firms have a profitable deviation and such a separating equilibrium does not exist.

[36] Assume that they are located at θ'' with $\theta'' < \theta'$. Since they buy from firm B at $p^B_{2,A}$, the initial costs are $p^B_{2,A} + (\bar{\theta} - \theta'')$, which is strictly larger than $p^B_{2,A} + (\bar{\theta} - \theta')$. By deviating to hide the cookies, the total costs would be $p^A_2 + \theta''$, which is strictly smaller than $p^A_2 + \theta'$. Combining together, we get that $p^A_2 + \theta'' < p^A_2 + \theta' = p^B_{2,A} + (\bar{\theta} - \theta') < p^B_{2,A} + (\bar{\theta} - \theta'')$, which shows the benefit from deviation.

Then we look at the scenario with just two segments in case (i). Figure 1.A.3 below describes such a scenario:

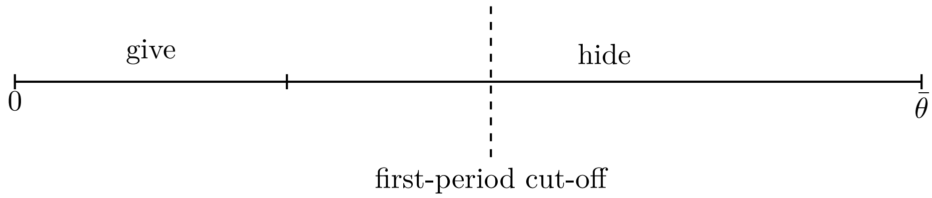


Figure 1.A.3: Line with two segments in case (i).

Firstly, we can show that in the “hide” segment there exists poaching behavior. Otherwise, one of the firm’s new customer prices should be 0, since both p_2^A and p_2^B are exclusively used in the “hide” segment and the firms have no reason to set a price above zero if they get no market share in this interval. If this were the case, the customers from the “give” segment would deviate to hide their cookies, since by doing so they could benefit from the zero new customer price. Secondly, similar to Lemma 1.A.1 we can prove that in the “give” segment no poaching behavior exists. In other words, all consumers buy from firm A at $p_{2,A}^A$, and $p_{2,A}^A = p_2^A$. However, firm A has an incentive to raise their loyalty price, in order to obtain more from loyal customers who grant access to their cookies. Thus, this structure of separating equilibrium is not possible. Combining these two scenarios, we can conclude that in case (i) (when the first-period cut-off goes through the “hide" segment) there is no separating equilibrium in pure strategies.

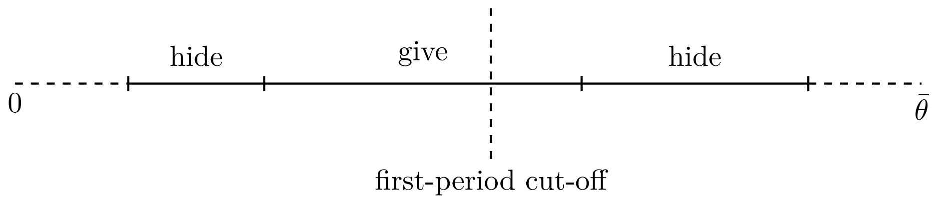


Figure 1.A.4: Line with multiple segments in case (ii).

In case (ii) when the first-period cut-off goes through the “give” segment, let’s first look at the scenario with multiple segments along the line. In Figure 1.A.4 above, by Lemma 1.A.1, there is no poaching behavior in all “hide” segments. This means that in the left “hide” segments firm A serves all customers at a price of p_2^A and in the right “hide” segments firm B serves all at a price of p_2^B. It is similar for all “give” segments on the sides, such that $p_2^A = p_{2,A}^A$ and $p_2^B = p_{2,B}^B$. Under such circumstances both firms have an incentive to increase their new customer prices p_2^A and p_2^B because this leads to a higher profit for “hide” segments while keeping “give” segments the same as before.[37] Hence, there is no separating equilibrium in pure strategies in this scenario.

[37]This situation is similar to a Hotelling line with discontinuous demands proposed by Ackley (1942) and Shilony (1977).

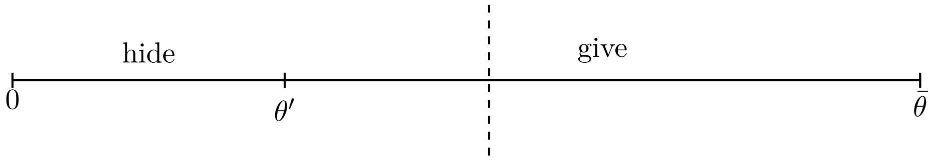


Figure 1.A.5: Line with two segments in case (ii).

Finally, we check the scenario with just two segments. Considering the interval between θ' and the first-period cut-off in Figure 1.A.5, there should exist poaching behavior. Otherwise, by the same logic mentioned before, either $p^A_{2,A}$ or $p^B_{2,A}$[38] is zero, and some outside customers deviate. Then similar to Lemma 1.A.1, we can easily show that no poaching behavior exists in the "hide" segment and all customers buy from firm A at p^A_2. In this condition firm A has an incentive to increase the new customer price, in order to get more profit from the "hide" segment. To sum it up, we prove that there is no separating equilibrium in pure strategies in case (ii) when the first-period cut-off goes through the "give" segment.

All the analyses above show that there is no separating equilibrium in pure strategies in the open data environment, which completes the proof of Proposition 1.2.

Open Data with Myopic Consumers

In the main analysis, we consider consumers to be strategic. Now we want to extend our analysis to a situation in which some consumers are myopic in the first stage with regard to their purchasing decision (Baye and Sapi, 2014, Carroni et al., 2015). We assume that there is a share α of myopic consumers and a share $1-\alpha$ of strategic consumers. For myopic consumers, their rationale is to choose the cheaper good in the first stage, however, they are strategic afterwards, including the cookie choice and the purchasing decision in the second stage. To the contrary, strategic consumers are always forward-looking in both stages. Therefore, the difference in this setting lies in the first stage, where, among myopic consumers, marginal consumer θ'_1 is just indifferent between buying from firm A at p^A_1 in stage 1 and buying from firm B at p^B_1 in stage 1, that is, $v - p^A_1 - \theta'_1 = v - p^B_1 - (\bar{\theta} - \theta'_1)$, leading to $\theta'_1 = \frac{\bar{\theta}}{2} + \frac{p^B_1 - p^A_1}{2}$. On the other hand, among strategic consumers,[39] the cut-off consumer θ_1 is indifferent between buying from firm A at p^A_1 in stage 1 and then buying from firm B at $p^B_{2,A}$ in stage 2, and buying from firm B at p^B_1 in stage 1 and then buying from firm A at $p^A_{2,B}$ in stage 2,[40] therefore,

$$v - p^A_1 - \theta_1 + \left[v - p^B_{2,A} - (\bar{\theta} - \theta_1)\right] = v - p^B_1 - (\bar{\theta} - \theta_1) + \left[v - p^A_{2,B} - \theta_1\right].$$

[38] This interval represents those who bought from firm A in the first stage and gave the cookies. Therefore, they are facing the loyalty price $p^A_{2,A}$ and poaching price $p^B_{2,A}$.

[39] To make it more precise, strategic consumers mean those who are forward-looking and reveal their data in the first stage.

[40] This indifference condition is the same as under open data with strategic consumers.

In order to solve this two-stage problem, we apply backward induction. Starting from the second stage, again there are two separated lines for consumers who did and who did not give their cookies, respectively. No matter whether they belong to the group of myopic consumers or the group of strategic consumers, the cut-offs are the same, since even myopic consumers are strategic in the second stage. Among those who granted access to their cookies in the first stage, the two cut-offs, θ_2^A and θ_2^B, are equivalent to $\frac{\bar{\theta}}{2}+\frac{p_{2,A}^B-p_{2,A}^A}{2}$ and $\frac{\bar{\theta}}{2}+\frac{p_{2,B}^B-p_{2,B}^A}{2}$, respectively.[41] Moreover, for those who did not give their cookies in the first stage, as we discussed before, they will face uniform pricing in the second stage, with $p_2^A=p_2^B=\bar{\theta}$ and $\theta_2=\frac{\bar{\theta}}{2}$.

Therefore, the competitors maximize their profits from the line with mass $1-\lambda$ as follows

$$\max_{p_{2,A}^A,p_{2,B}^A} \quad \alpha(1-\lambda)\left[p_{2,A}^A\theta_2^A+p_{2,B}^A(\theta_2^B-\theta_1')\right]+(1-\alpha)(1-\lambda)\left[p_{2,A}^A\theta_2^A+p_{2,B}^A(\theta_2^B-\theta_1)\right],$$

$$\max_{p_{2,B}^B,p_{2,A}^B} \quad \alpha(1-\lambda)\left[p_{2,B}^B(\bar{\theta}-\theta_2^B)+p_{2,A}^B(\theta_1'-\theta_2^A)\right] + (1-\alpha)(1-\lambda)\left[p_{2,B}^B(\bar{\theta}-\theta_2^B)+p_{2,A}^B(\theta_1-\theta_2^A)\right].$$

Lemma 1.A.2 *Combining these two optimization problems and deriving the first order conditions, we obtain the following prices in the second stage*

$$p_{2,A}^A=\frac{\bar{\theta}}{3}+\frac{2}{3}\theta_1+\frac{2}{3}\alpha(\theta_1'-\theta_1), \qquad p_{2,B}^A=\bar{\theta}-\frac{4}{3}\theta_1+\frac{4}{3}\alpha(\theta_1-\theta_1'),$$

$$p_{2,B}^B=\bar{\theta}-\frac{2}{3}\theta_1+\frac{2}{3}\alpha(\theta_1-\theta_1'), \qquad p_{2,A}^B=-\frac{\bar{\theta}}{3}+\frac{4}{3}\theta_1+\frac{4}{3}\alpha(\theta_1'-\theta_1).$$

Note that on the line with consumer mass λ, nothing changes and therefore the prices correspond to uniform pricing.

On the first stage, the cut-offs are different among the myopic consumers and strategic consumers, and also depend on whether they decline cookies or not. Therefore, there are four groups of different consumers. Among the mass of λ consumers who do not share their information, a mass of $\alpha\lambda$ are myopic and a mass of $(1-\alpha)\lambda$ are strategic. However, no matter whether they are myopic or strategic, the cut-offs they face are the same, that is $\theta_1'=\frac{\bar{\theta}}{2}+\frac{p_1^B-p_1^A}{2}$.[42] Similarly, among the mass of $1-\lambda$ consumers, there are $\alpha(1-\lambda)$ myopic consumers facing the cut-off of θ_1', while a mass of $(1-\alpha)(1-\lambda)$ are strategic consumers with the cut-off of θ_1.

Combining these indifference conditions and the results from Lemma 1.A.2, we obtain $\theta_1'=\frac{\bar{\theta}}{2}+\frac{p_1^B-p_1^A}{2}$ and $\theta_1=\frac{\bar{\theta}}{2}-\frac{4\alpha-3}{8(1-\alpha)}(p_1^B-p_1^A)$. Maximizing the overall profits in the first period with respect to the first-stage prices, the two firms have the

[41] The method to derive these cut-offs are identical to the open data environment with strategic consumers.

[42] θ_1' will not be influenced by the prices in the second stage, which is similar to the open data environment with strategic consumers.

resulting objective functions

$$\pi^A = \alpha\big[\lambda p_1^A\theta_1' + (1-\lambda)p_1^A\theta_1' + \lambda p_2^A\theta_2 + (1-\lambda)p_{2,A}^A\theta_2^A + (1-\lambda)p_{2,B}^A(\theta_2^B - \theta_1')\big]$$

$$+ (1-\alpha)\big[\lambda p_1^A\theta_1' + (1-\lambda)p_1^A\theta_1 + \lambda p_2^A\theta_2 + (1-\lambda)p_{2,A}^A\theta_2^A + (1-\lambda)p_{2,B}^A(\theta_2^B - \theta_1)\big],$$

$$\pi^B = \alpha[\lambda p_1^B(\bar{\theta} - \theta_1') + (1-\lambda)p_1^B(\bar{\theta} - \theta_1') + \lambda p_2^B(\bar{\theta} - \theta_2) + (1-\lambda)p_{2,B}^B(\bar{\theta} - \theta_2^B)$$

$$+ (1-\lambda)p_{2,A}^B(\theta_1' - \theta_2^A)] + (1-\alpha)\big[\lambda p_1^B(\bar{\theta} - \theta_1') + (1-\lambda)p_1^B(\bar{\theta} - \theta_1) + \lambda p_2^B(\bar{\theta} - \theta_2)$$

$$+ (1-\lambda)p_{2,B}^B(\bar{\theta} - \theta_2^B) + (1-\lambda)p_{2,A}^B(\theta_1 - \theta_2^A)\big].$$

Corollary 1.A.2 *Substituting the respective prices into the system of equations given by the first-order conditions, we derive the final results for the first- and second-stage prices:*

$$p_1^A = p_1^B = \frac{4}{3+\lambda}\bar{\theta}, \qquad p_{2,A}^A = p_{2,B}^B = \frac{2}{3}\bar{\theta},$$

$$p_{2,B}^A = p_{2,A}^B = \frac{1}{3}\bar{\theta}, \qquad p_2^A = p_2^B = \bar{\theta}.$$

Everyone chooses to give cookies, therefore the optimal λ is 0 and the resulting prices are identical to the open data environment with strategic consumers.

The result above is a robustness check, showing that being strategic or myopic in the first period purchase does not affect any decisions. Consumers choose to grant firms access to their cookies, in order to benefit from competition; while firms use standard behavior-based price discrimination to maximize their profits. Moreover, the strategic cookie choice is sufficient to yield identical results including first period prices. This is not the case in standard behavior-based pricing models without the cookie stage.

Open Data Environment with Quadratic Transportation Costs

In this variation of the model, the utility for a consumer located at θ is either $v - p^i - \theta^2$ if buying from firm A, or $v - p^j - (\bar{\theta} - \theta)^2$ if buying from firm B. As in the standard model, we employ backward induction and finally find that $p_1^A = p_1^B = \frac{4}{3+\lambda}\bar{\theta}^2$, and $\theta_1 = \frac{1}{2}\bar{\theta}$, $p_{2,A}^A = p_{2,B}^B = \frac{2}{3}\bar{\theta}^2$, $p_{2,B}^A = p_{2,A}^B = \frac{1}{3}\bar{\theta}^2$. If the cost is quadratic in the standard behavior-based pricing model, prices in the first stage are $p_1^A = p_1^B = \frac{4}{3}\bar{\theta}^2$, and the uniform pricing strategy is $p_1^A = p_1^B = \bar{\theta}^2$. Prices reflect quadratic transportation costs. Thus, each buyer reveals their cookies, $\lambda = 0$, in order to get the lower price in the second stage and thus all the results in the open data environment hold with quadratic transportation costs.

Proof of Lemma 1.2

When maximizing the profit functions of the second stage, we get the following expressions for the first-order conditions:

$$\frac{\partial \pi_2^A}{\partial p_2^A} = \frac{\lambda}{2}(p_2^B - 2p_2^A + \bar{\theta}) + \frac{(1-\lambda)}{2}(p_{2,B}^B - 2p_2^A + \bar{\theta}) - (1-\lambda)\bar{\theta} = 0,$$

$$\frac{\partial \pi_2^A}{\partial p_{2,A}^A} = \frac{(1-\lambda)}{2}(p_2^B - 2p_{2,A}^A + \bar{\theta}) = 0,$$

$$\frac{\partial \pi_2^B}{\partial p_2^B} = \frac{\lambda}{2}(-2p_2^B + p_2^A + \bar{\theta}) + \frac{(1-\lambda)}{2}(-2p_2^B + p_{2,A}^A - \bar{\theta} + 2\theta_1) = 0,$$

$$\frac{\partial \pi_2^B}{\partial p_{2,B}^B} = \frac{(1-\lambda)}{2}(-2p_{2,B}^B + p_2^A + \bar{\theta}) = 0.$$

This gives a system of equations, where prices are dependent on each other and need to be substituted into each other in order to receive the final set of prices of the second period that are only depending on λ, p_1^A and p_1^B:

$$p_{2,A}^A(p_2^B) = \frac{\bar{\theta} + p_2^B}{2},$$

$$p_2^A(p_2^B) = \frac{(3-\lambda)\bar{\theta} + 2\lambda \cdot p_2^B - 4(1-\lambda)\theta_1}{3+\lambda},$$

$$p_{2,B}^B(p_2^A) = \frac{\bar{\theta} + p_2^A}{2},$$

$$p_2^B(p_2^A) = \frac{-(1-3\lambda)\bar{\theta} + 2\lambda \cdot p_2^A + 4(1-\lambda)\theta_1}{3+\lambda}.$$

Please note that unlike Lemma 1.1, we do not need to consider the corner solution here. In the open data environment, the poaching price from one firm may be zero, but in the exclusive data environment, firms cannot poach and use the new customer price instead. For any firm i, setting the price p_2^i at zero is a weakly dominated strategy since its marginal cost is just zero. However, when the information is exclusive, the new customer price is also applied to those who hide their cookies. Considering the firm i again, if the new customer price from another firm p_2^j is not zero, they always have an incentive to set the price above zero in order to get some profits from those who hide their cookies, which will make them strictly better off than choosing the corner solution. Thus, we do not consider the corner solution in the exclusive data environment. All the equations above can easily derive the results in Lemma 1.2.

Proof of Proposition 1.3

In the case where all consumers hide their information, the counterfactual of consumers who disclose information is governed by off-path beliefs. Suppose, without loss of generality, a single (atom-less) consumer who bought from A in period 1 deviates by disclosing information. The price setting of firm B remains unchanged, since B cannot target the deviating consumer and the impact on the price is negligible. This consumer who identifies towards A can only be located on $[0, \theta_1]$ and will receive a price from firm A to make him indifferent between buying from firm A and firm B. Thus, the utility $\tilde{u}(\theta)$ of a consumer of type θ who deviates is:

$$\tilde{u}(\theta)^{43} = \begin{cases} v - 2\bar{\theta} + \theta & \text{if} \quad \theta \leq \dfrac{\bar{\theta}}{2} \\ v - \bar{\theta} - \theta & \text{if} \quad \theta \geq \dfrac{\bar{\theta}}{2}. \end{cases}$$

From the firm's side, their belief about who may deviate depends on the utilities that the consumer get with and without deviating. By Proposition 1.3 and the utility with deviation $\tilde{u}(\theta)$ derived above, we check different scenarios separately: when $0 \leq \theta < \frac{\bar{\theta}}{2}$, the utility of a consumer of type θ without deviation is $v - \bar{\theta} - \theta$, which is strictly larger than the utility $\tilde{u}(\theta)$ if they deviate, that is $v - 2\bar{\theta} + \theta$. When $\frac{\bar{\theta}}{2} < \theta \leq \bar{\theta}$, the utility of a consumer of type θ without deviation is $v - \bar{\theta} - (\bar{\theta} - \theta)$, which is strictly larger than the utility $\tilde{u}(\theta)$ if they deviate, that is $v - \bar{\theta} + \theta$. Only when $\theta = \frac{\bar{\theta}}{2}$, the utility of a consumer of type θ does not change with or without the deviation, as shown in Figure 1.A.6 at hands of the total costs $v - \tilde{u}(\theta)$.

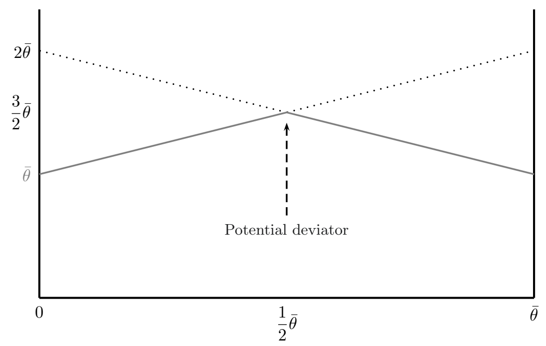


Figure 1.A.6: Total costs in equilibrium (solid) and for individual deviators (dotted).

Corollary 1.A.3 *If firms observe any deviation from consumers, they form the off-path belief that it is the consumer located at $\frac{\bar{\theta}}{2}$ and set the off-path price $\bar{\theta}$ as a best response.*

[43] Please note the firm that the deviating consumer did not buy from in the first stage sets the price at $\bar{\theta}$ and this consumer is indifferent between buying from either firm.

Since only the consumer in the center of the line gets the same utility from deviating, firms' best response is to set the uniform price $\bar{\theta}$. However, consumers do not benefit from the deviation, since the utility does not change. Therefore, the proof is complete.

Proof of Proposition 1.4

In this section, we look at the exclusive data environment, where similar arguments compared to the proof of Proposition 1.2 are applied to prove that there is no separating equilibrium in pure strategies. To do so we first expand Lemma 1.A.1 to the case of exclusive data.

Lemma 1.A.3 *If there exists a separating equilibrium for a line with multiple segments under exclusive data, there is no poaching behavior in the lateral segments.*

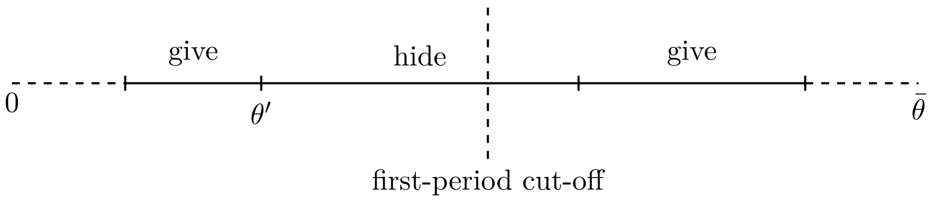


Figure 1.A.7: Line with multiple segments in case (i).

Proof. Let's take Figure 1.A.7 as an example where the first-period cut-off divides a "hide" segment. Assume towards a contradiction that there exists poaching behavior in the left segment. This means that consumers to the left of θ' buy from firm B at p_2^B and to the right of θ' buy from firm A at p_2^A. The consumer located at θ' is indifferent between accepting and declining cookies. The cost of each option should be the same for this indifferent consumer, i.e., $p_2^B + (\bar{\theta} - \theta') = p_2^A + \theta'$. However, consumers located to the left of θ' who buy from firm B at p_2^B, have an incentive to deviate. By deviating to hide cookies, the total cost of buying from firm A would be strictly smaller than the cost before.[44] The same method can be applied to the case when the first-period cut-off divides the "give" segment, which together shows that if there is poaching behavior in the lateral segments, consumers have an incentive to deviate, such that a separating equilibrium in pure strategies cannot exist. ■

From Lemma 1.A.3 we can generally infer that in a separating equilibrium firms give up their option to price discriminate since the cut-offs between lateral segments the following must hold: $p_2^i = p_{2,i}^i$, $\forall i = A, B$. Based on Lemma 1.A.3, we show the non-existence of a separating equilibrium in pure strategies under exclusive data.

Similar to the previous proof of Proposition 1.2, we distinguish between two cases: (i) when the first-period cut-off divides a "hide" segment, and (ii) when the

[44]Assume that they are located at θ'' with $\theta'' < \theta'$. Since they buy from Firm B at p_2^B, the initial costs are $p_2^B + (\bar{\theta} - \theta'')$, which is strictly larger than $p_2^B + (\bar{\theta} - \theta')$. By deviating to hide their data, the total costs would be $p_2^A + \theta''$, which is strictly smaller than $p_2^A + \theta'$. Combining together we can get that $p_2^A + \theta'' < p_2^A + \theta' = p_2^B + (\bar{\theta} - \theta') < p_2^B + (\bar{\theta} - \theta'')$, which shows the benefit from deviation.

first-period cut-off divides a "give" segment. Combining with the number of the segments along the line, we need to, again, check four possible scenarios separately.

Let's first consider case (i) with multiple segments. As mentioned in Figure 1.A.7, we assume towards a contradiction that there is a separating equilibrium with pure strategies. In order for such a separating equilibrium to exist Lemma 1.A.3 must hold and poaching behavior in lateral segments is excluded, which means that firms cannot poach with their new customer prices in "give" segments. Again, this implies that firms give up the option to price discriminate in pure-strategy separating equilibria, which is directly shown from $p_2^i = p_{2,i}^i$. Yet, it is obvious that firms have an incentive to price discriminate on consumers who share their cookies. By increasing their loyalty prices when consumers are segmented as in the figure above, firms gain by giving up less rent to the consumers. This is a direct contradiction to the existence of a possible separating equilibrium.

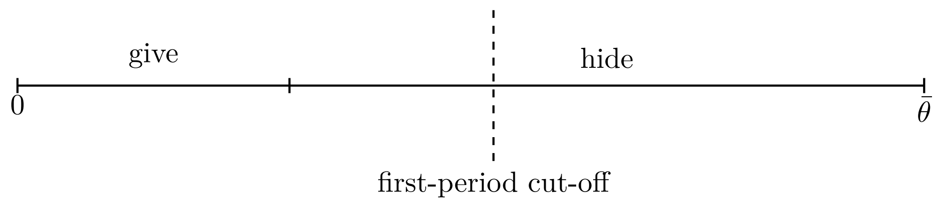


Figure 1.A.8: Line with two segments in case (i).

Then we look at the scenario with just two segments in case (i). If there exists such a separating equilibrium as in Figure 1.A.8, from Lemma 1.A.3 we find no poaching behavior in the "give" segment. Moreover, based on the customer indifferent between hiding and accepting cookies, we have $p_{2,A}^A = p_2^A$. Please note that under such circumstances the firms again give up price discrimination. However, firm A has an incentive to raise the loyalty price $p_{2,A}^A$. By doing so, they get more profit from loyal customers and not affect the profit from anonymous customers. Therefore, this structure is not possible and we can conclude that there is no separating equilibrium in pure strategies in case (i).

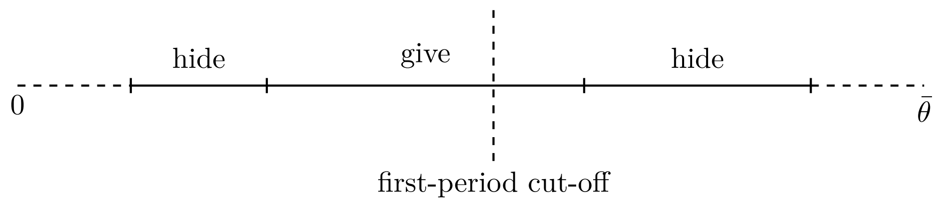


Figure 1.A.9: Line with multiple segments in case (ii).

In case (ii) when the first-period cut-off divides a "give" segment, let's first look at the scenario with multiple segments along the line. In Figure 1.A.9, by Lemma 1.A.3 we know that there is no poaching behavior in the lateral segments. This means that $p_{2,A}^A = p_2^A$ and $p_{2,B}^B = p_2^B$, and firms give up their option to price discriminate in the lateral segments. Now, we focus on the central "give" segment. To the left of the first-period cut-off, all consumers face $p_{2,A}^{A}$ from firm A and p_2^B from firm B. Similarly, to the right of this cut-off, all consumers choose between p_2^A from firm A and $p_{2,B}^{B}$ from firm B. Given the fact that $p_{2,A}^{A} = p_2^A$ and $p_{2,B}^{B} = p_2^B$, the second-period cut-offs in these two intervals coincide, which means that $\theta_2^A = \theta_2^B$. Considering the location of θ_2^A and θ_2^B, there are three possibilities: to the left of the first-period cut-off, to the right of the first-period cut-off, and coinciding with the first-period cut-off.[45] If θ_2^A and θ_2^B are to the left of the first-period cut-off, no consumers located to the right of the first-period cut-off buy from firm A at p_2^A. However, in such a condition, firm A has an incentive to raise p_2^A in order to get more profit. Thus, we can rule out this possibility. Similarly, if θ_2^A and θ_2^B are to the right of the first-period cut-off, no consumers located to the left of the first-period cut-off will buy from firm B at p_2^B and firm B would like to increase their new customer price. Therefore, this possibility is also excluded. Finally, if θ_2^A and θ_2^B coincide with the first-period cut-off, no customers in the central "give" segment buy from firm A at p_2^A or from firm B at p_2^B. Under such circumstances, both firm A and firm B have an incentive to raise their new customer prices and they benefit from this deviation. Overall, we have shown that no separating equilibrium exists in this scenario.

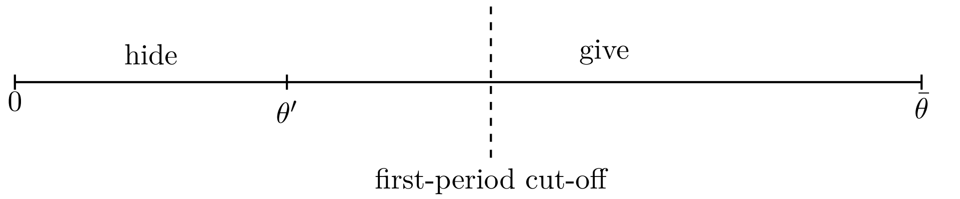


Figure 1.A.10: Line with two segments in case (ii).

Finally, we check the scenario with just two segments when the first-period cut-off divides the "give" segment. Firstly, in the "give" segment, there should be some consumers buying from firm A at $p_{2,A}^{A}$ and some buying from firm B at $p_{2,B}^{B}$. Otherwise, since $p_{2,A}^{A}$ and $p_{2,B}^{B}$ are exclusively set in this segment, either $p_{2,A}^{A}$ or $p_{2,B}^{B}$ should be zero and some outside consumers will deviate to this interval. Then, similar to Lemma 1.A.3, we can easily show that there is no poaching behavior in the "hide" segment and $p_2^A = p_{2,A}^{A}$. Under such circumstances, there are two groups of consumers buying from firm A at p_2^A on this line: those who choose to decline cookies and those who accept cookies and buy from firm B in the first stage. Apparently, due to the higher transportation cost, the second group of consumers has an incentive to deviate. They would choose to hide cookies in the first stage, and the structure of this separating equilibrium collapses accordingly. As a summary, we can conclude that no separating equilibrium in pure strategies exists in case (ii). This completes the proof.

[45] Please note that θ_2^A and θ_2^B do not need to be within the central "give" segment. All results hold even if they are not within the central "give" segment.

1.B Appendix B: Experiment

Instructions for the Market Game - Exclusive Data [Open Data][46]

A market

Participants take the role of buyers or sellers and are active in a market with eight locations. Two sellers sell the same good and are located on either end of the market. Six buyers are located between the two sellers according to the following graphical depiction:

Seller	**Buyer**	**Buyer**	**Buyer**	**Buyer**	**Buyer**	**Buyer**	**Seller**
Location 1	Location 2	Location 3	Location 4	Location 5	Location 6	Location 7	Location 8

Buyers buy exactly one good in each of the two periods. Sellers choose prices p at the beginning of each period. Prices must be integers between 0 and 10. Buyers pay the price of a good and transportation costs t according to their distance to the respective seller. Buyers pay transportation costs of one unit per field and have to move to the sellers' location. Buyers receive earnings according to the following earnings function:

$$Earnings = 15 - p - t$$

At the beginning of the first period, sellers choose an *introduction price.* Buyers choose one seller and decide whether to allow *cookies.* At the beginning of the second period, sellers choose three prices: a *loyalty price*[, a *poaching price*] and a *new customer price.* The profit of sellers in a market corresponds to the sold number of goods multiplied with their respective price according to the following profit function:

$$Profit = p \cdot n$$

The following table depicts which buyer sees which price of the two sellers in the second period, according to their initial purchasing decision and cookie choice.

Chosen seller in first period	Allow use of cookies	Price of seller 1	Price of seller 2
Seller 1	allow	Loyalty price	New customer price
Seller 1	don't allow	New customer price	New customer price
Seller 2	allow	New customer price	Loyalty price
Seller 2	don't allow	New customer price	New customer price

[Differences in the open data treatment <u>underlined</u>.]

[46]Here you find translated versions of the instrutions for the experiment. Original instructions are in German and can be made available upon request. Note that transportation costs in the instructions are denoted by t which corresponds to θ in the main body.

Chosen seller in first period	Allow use of cookies	Price of seller 1	Price of seller 2
Seller 1	allow	Loyalty price	Poaching price
Seller 1	don't allow	New customer price	New customer price
Seller 2	allow	Poaching price	Loyalty price
Seller 2	don't allow	New customer price	New customer price

Procedure

At the beginning of the experiment each participant is assigned a role, which remains fixed for the remainder of the experiment of 20 rounds in total. In each round there are two markets with two sellers each. Six buyers are active in **both** markets, while sellers are active in **one** of the markets. Within one round locations of buyers and sellers are fixed. Each round buyers are assigned random new locations in both markets. Sellers are randomly assigned to one market with a random location at either end of the market in each round.

The Game of 22

The iterative thinking task is a variation of the "Game of 21" (Dufwenberg et al., 2010, Gneezy et al., 2010). In our version, players take turns increasing a counter that starts at 0 by increments of 1, 2 or 3. The game ends when either of two players reaches 22, where the player who picks 22 loses. Thereby, the game stays true to the original variation, where the player who picks 21 wins the game directly. The winning path constitutes of picking any number that is a multiple of three. Instead of using an interactive game between two subjects, as intended in the original variation, we let each subject play against the computer. This is necessary in order to gather a measure on correct iterative reasoning for every subject.[47] Subjects learn that they play against the computer, without any detailed explanation on how the computer chooses. Unknown to the players, the computer avoids winning, while randomizing between the two or three available options[48]. This is necessary so that we can capture the exact turn in which participants realized how to win the game.

Instructions for the Game of 22[49]

The rules of the game are as follows: This is a two-player game in which players increase a counter. This counter starts at zero and ends at 22 and must be moved each turn by one, two or three steps, with players acting sequentially. You will play this game against the computer and you are the first to move. The player who

[47] If two players interact and one plays the optimal strategy, no conclusions can be drawn concerning the other player.

[48] Whenever the player is on the winning path, the computer randomizes between all three options, while only randomizing between the two options which avoid the winning path, whenever the player is not on the winning path.

[49] Instructions are originally in German and presented on screen.

reaches 22 loses. If the computer loses the game, you will earn EUR 2, while you will earn EUR 0 if you lose.

0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**

Figure 1.B.1: Representation of the Game of 22.

Results of the Game of 22

Figure 1.B.4 shows the distribution of scores in the Game of 22. The score represents the number of consecutive turns on the winning path before the game ended. Our findings are in line with Dufwenberg et al. (2010) where the majority of subjects are able to solve two steps of backward induction (*mean: 2.01, median: 2, mode: 2*). In contrast to their results, our subjects did not show an ability to immediately solve the game, with barely anyone solving the full six steps of induction. Overall, the results suggest that the game is suitable as a rough measure of iterative thinking capability and we cannot detect any differences between our treatments, $\chi^2(6, N = 80) = 0.8359, p = 0.991$.

Privacy Concern Survey (IUIPC Score)[50]

All statements are rated by the subjects on a seven-point scale from “strongly agree” to “strongly disagree”. The first three statements relate to control issues, statements four to six relate to awareness and the remaining four statemtents relate to collection issues.

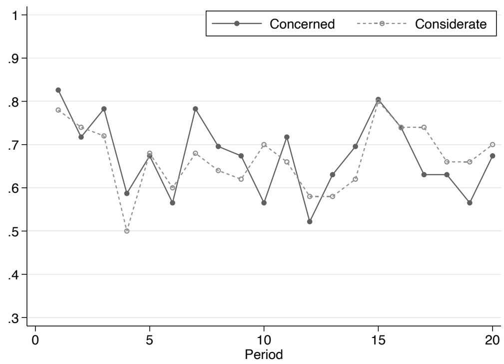
1) Consumer online privacy is really a matter of consumers’ right to exercise control and autonomy over decisions about how their information is collected, used, and shared.
2) Consumer control of personal information lies at the heart of consumer privacy.
3) I believe that online privacy is invaded when control is lost or unwillingly reduced as a result of a marketing transaction.
4) Companies seeking information online should disclose the way the data are collected, processed, and used.
5) A good consumer online privacy policy should have a clear and conspicuous disclosure.
6) It is very important to me that I am aware and knowledgeable about how my personal information will be used.
7) It usually bothers me when online companies ask me for personal information.

[50] Original questions of Malhotra et al. (2004) were translated into German.

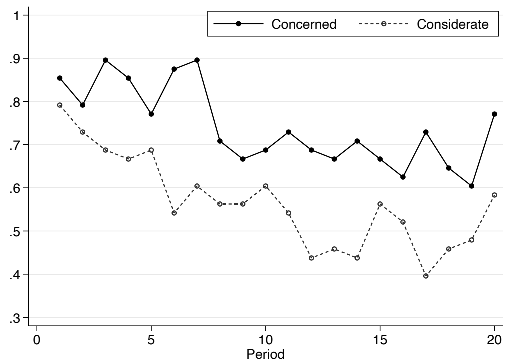
8) When online companies ask me for personal information, I sometimes think twice before providing it.
9) It bothers me to give personal information to so many online companies.
10) I'm concerned that online companies are collecting too much personal information about me.

The Role of Privacy Concern

In this section, we take a deeper look into our control measure of privacy concern and how it relates to information disclosure. Our observed IUIPC-scores are depicted in Figure 1.B.5. The distributions do not show treatment differences, $t(158) = 1.4147, p = 0.1591$. However, there is a tendency towards high privacy concern among our subjects. Going forward, we classify our subjects into three groups, using the median (0.2014) as an initial breaking point and 1-median ($1 - 0.2014 = 0.7986$) as the second breaking point. We classify a score below the median as "privacy concerned", a score between the median and 1-median as "privacy considerate", and a score above 1-median as "privacy unconcerned". By nature of this classification, half of our subjects fall into the first category of concerned, while surprisingly not a single subject falls into the last category of unconcerned. Thus, the remaining half of the subjects are "considerates".[51]



(a) Open data treatment



(b) Exclusive data treatment

Figure 1.B.2: Share of tracking allowed over periods by Treatment and privacy concern.

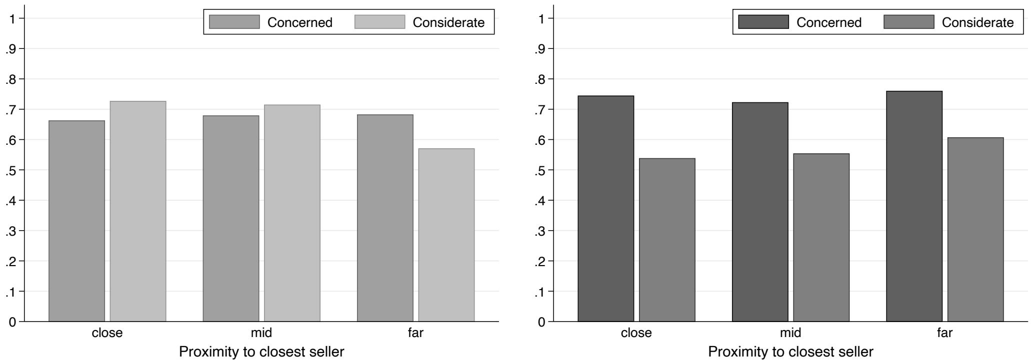
In Figure 1.B.2, we show the average rate of information disclosure over period by treatment and privacy concern classification. There are two major observations here. In the open data treatment, "concerned" and "considerate" buyers have a similar sharing rate. In the exclusive data treatment, "considerate" subjects have a lower sharing rate than "concerned" subjects, which relates to the *privacy paradox*.[52] Moreover, we find that the initially large sharing rate in the exclusive data treatment is largely driven by "concerned" subjects.

Beresford et al. (2012) and Preibusch et al. (2013) find that subjects did not act according to their stated privacy preferences when faced with a market environment. This is also reflected in Figure 1.B.2, where more concerned participants are actually sharing more information. However, for both privacy concerned and considerate buy-

[51]Among the considerates, we also observe a tendency leaning towards privacy concern. Moreover, irrespective of the final score all subjects expressed concern at least once within the 10 item questionnaire.

[52]Acquisti et al. (2016) and Dinev and Hart (2006) explain the paradox with a *privacy calculus* model, which describes a mental negotiation of benefits versus concerns from disclosing information in an e-commerce setting.

ers we see a drop in information sharing over periods, where particularly considerate buyers in the exclusive data treatment drop below the sharing rates of the remaining three groups in the last ten rounds.



(a) Open data treatment (b) Exclusive data treatment

Figure 1.B.3: Share of tracking allowed per location by Treatment and privacy concern.

Next, we investigate whether similar discrepancies are present in the locational information disclosure between privacy types. In Figure 1.B.3, we show how information disclosure depends on consumers' locations under classification between privacy types. This ties in directly with our theoretical analysis which largely relies on the *pooling* assumption in the construction of equilibria. Again, we differentiate between "concerned" and "considerate" consumers. Figure 1.B.3 depicts that there is no locational preference for information disclosure in case of "concerned" consumers for both treatments. However, "considerate" consumers share less information than "concerned" consumers in the exclusive data treatment. This is true for all locations and is considerably balanced.

The time trend did not reveal an impact of privacy concern on information disclosure in the open data treatment, but we find an impact of location in the case of considerate consumers. Considerate subjects in the open data treatment are less likely to share information at the "far" location than concerned subjects, $\chi^2(2, N = 670) = 7.50, p < 0.03$. In comparison to concerned consumers we find that considerate consumers share slightly more information in close and mid locations and less information in the far location.[53] These counteracting effects cancel each other out, so that the average disclosure rate of considerate consumers is similar to the disclosure rate of concerned consumers. While we cannot explain this behavior on theoretical grounds, we can suggest that considerate consumers are more involved when it comes to disclosure of private information and both data environments (open and exclusive data) and the individual preferences (where preferences are described by location) are factored into the decision. Overall, this extends our evidence towards

[53]These deviations relate to Lemma 1.A.1 in that the most probable deviations are suspected in the central locations. The according response by sellers is setting the loyalty price equal to the new customer price. This corresponds to the pricing observations we have shown earlier.

Hypothesis 3. That is, we observe less information sharing in the exclusive data treatment, which is mainly driven by privacy "considerate", i.e. less concerned subjects. This is akin to the commonly observed *privacy paradox*. Those who express more concern about privacy issues are not consistently acting on it.

In Table 1.B.3, we include a *Considerate* dummy, as well as an interaction of *Considerate* with the treatment and second-half dummies. The main effects that we have shown in Table 1.8 still hold when allowing for this richer interaction with privacy concern. Moreover, we can confirm the results we discussed before. Considerates share less information in the exclusive treatment overall, whereas this effect is weakened in the far location. Considerates share less information in the far location in the open data treatment.

Additional Figures and Tables

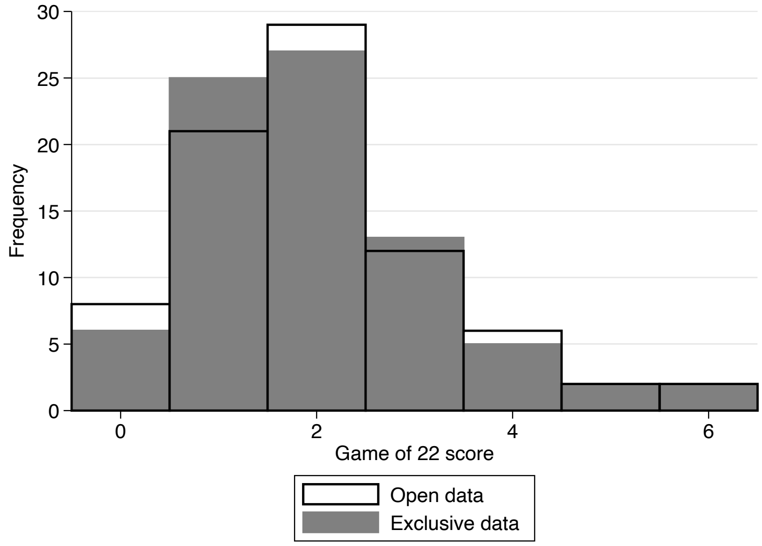


Figure 1.B.4: Game of 22 scores by Treatment.

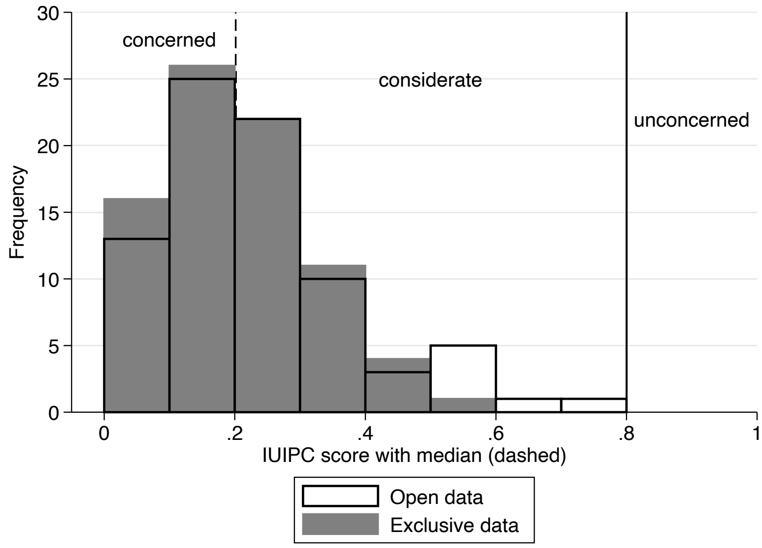


Figure 1.B.5: IUIPC scores by Treatment.

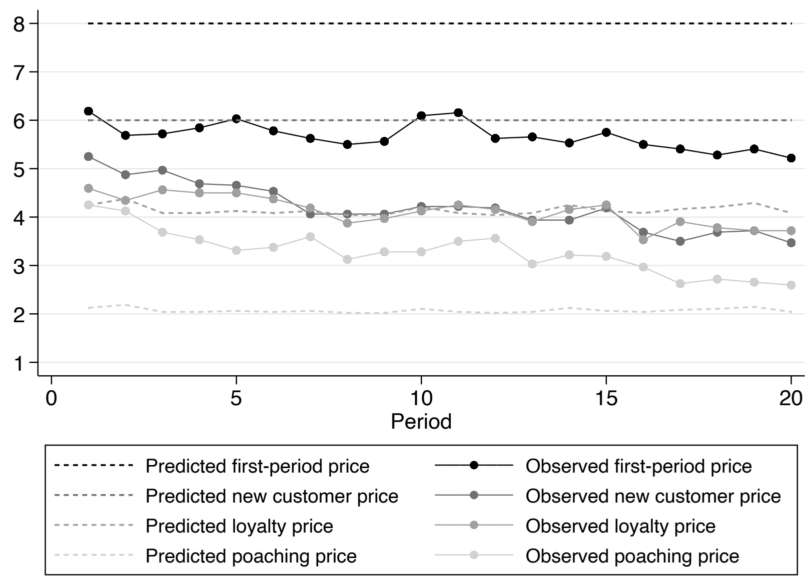


Figure 1.B.6: Observed and predicted prices in the open data treatment.

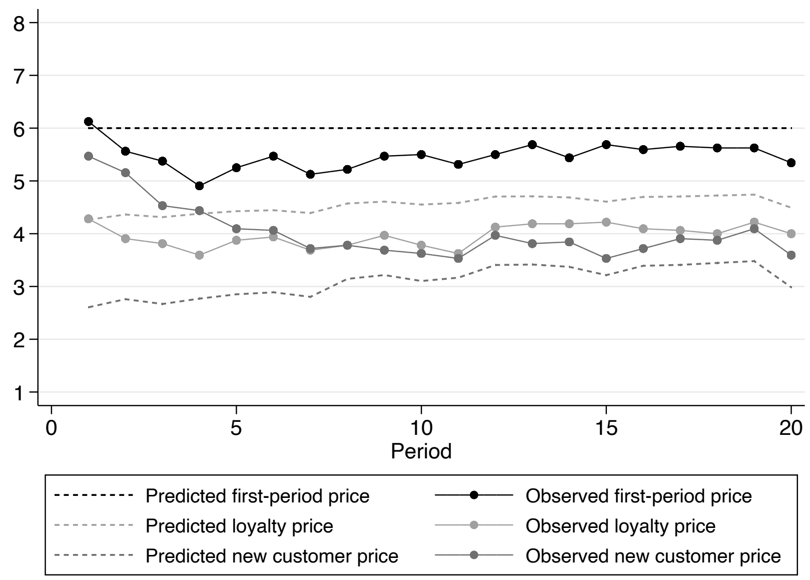


Figure 1.B.7: Observed and predicted prices in the exclusive data treatment.

	Location						
	2	3	4	5	6	7	Total
Open data treatment							
Purchasing order (b_1, b_2)							
(A, A)	92.50%	83.12%	43.12%	5.62%	1.88%	0.31%	37.76%
(A, B)	3.12%	9.06%	25.94%	20.94%	7.50%	0.94%	11.25%
(B, A)	2.81%	5.62%	23.12%	29.38%	1.88%	0.31%	11.93%
(B, B)	1.56%	2.19%	7.81%	44.06%	83.44%	95.31%	39.06%
Information disclosure	67.50%	69.38%	62.81%	61.88%	70.00%	71.56%	67.19%
Exclusive data treatment							
Purchasing order (b_1, b_2)							
(A, A)	96.25%	89.38%	57.50%	10.31%	0.94%	0.62%	42.50%
(A, B)	2.19%	3.75%	18.75%	18.12%	7.19%	2.50%	8.75%
(B, A)	1.56%	5.31%	14.69%	15.31%	3.44%	1.56%	6.98%
(B, B)	0.00%	1.56%	9.06%	56.25%	88.44%	95.31%	41.77%
Information disclosure	60.94%	62.19%	69.38%	67.19%	65.31%	67.19%	65.36%

Seller A is located at location 1, seller B is located at location 8, just outside the depicted locations. (b_1, b_2) is the purchase order, where $b_1 \in \{A, B\}$ is the first period purchase and $b_2 \in \{A, B\}$ is the second period purchase.

Table 1.B.1: Share of purchasing orders and information disclosure by treatment and location.

	Bought from far seller in period 1 at same total costs $\in \{0, 1\}$			
	(1)	(2)	(3)	(4)
Exclusive	-1.168***	-1.194***	-1.192***	-1.198***
	(0.408)	(0.398)	(0.407)	(0.397)
Tracking			0.404	0.489
			(0.342)	(0.361)
Second half			0.226	0.177
			(0.292)	(0.299)
Market	No	Yes	No	Yes
Location	No	Yes	No	Yes
Demographics	No	Yes	No	Yes
Privacy concern	No	Yes	No	Yes
Iterative thinking	No	Yes	No	Yes
Observations	310	297	310	297

Standard errors in parentheses. Estimation by multilevel mixed-effects logistic regression with hierarchical clustering on group and subject level. *, ** and *** denote significance at the 10 %, 5 % and 1 % level, respectively.

Table 1.B.2: Impact of treatment, tracking and learning on purchasing decision when total costs are equal.

	Dependent variable: Tracking allowed $\in \{0,1\}$					
	Privacy concern × Learning		Privacy concern × Location		Privacy concern × (Learning + Location)	
	(1)	(2)	(3)	(4)	(5)	(6)
Exclusive	0.891**	0.948*	0.585	0.624	0.931**	0.963*
	(0.409)	(0.513)	(0.417)	(0.517)	(0.442)	(0.540)
Considerate	-0.065	-0.264	0.279	0.074	0.181	-0.027
	(0.397)	(0.373)	(0.408)	(0.387)	(0.429)	(0.407)
Exclusive × Considerate	-0.900	-1.121**	-1.537***	-1.748***	-1.428**	-1.644***
	(0.568)	(0.526)	(0.580)	(0.542)	(0.613)	(0.574)
Second half	-0.142	-0.143			-0.144	-0.144
	(0.154)	(0.154)			(0.154)	(0.154)
Exclusive × Second half	-0.626***	-0.621***			-0.625***	-0.621***
	(0.229)	(0.228)			(0.229)	(0.229)
Considerate × Second half	0.187	0.187			0.194	0.193
	(0.215)	(0.214)			(0.215)	(0.215)
Exclusive × Considerate	-0.265	-0.282			-0.278	-0.293
× Second half	(0.313)	(0.313)			(0.314)	(0.314)
Mid			0.094	0.102	0.094	0.102
			(0.194)	(0.195)	(0.195)	(0.195)
Far			-0.041	-0.043	-0.042	-0.045
			(0.188)	(0.188)	(0.188)	(0.188)
Exclusive × Mid			-0.128	-0.125	-0.125	-0.121
			(0.280)	(0.280)	(0.282)	(0.282)
Exclusive × Far			-0.001	0.007	-0.000	0.007
			(0.278)	(0.278)	(0.281)	(0.280)
Concerned × Mid			-0.180	-0.182	-0.180	-0.181
			(0.272)	(0.271)	(0.272)	(0.272)
Considerate × Far			-0.561**	-0.549**	-0.561**	-0.548**
			(0.264)	(0.263)	(0.264)	(0.263)
Exclusive × Considerate			0.514	0.513	0.513	0.509
× Mid			(0.386)	(0.386)	(0.390)	(0.389)
Exclusive × Considerate			1.074***	1.063***	1.090***	1.078***
× Far			(0.383)	(0.383)	(0.386)	(0.386)
Market	No	Yes	No	Yes	No	Yes
Demographics	No	Yes	No	Yes	No	Yes
Iterative thinking	No	Yes	No	Yes	No	Yes
Observations	3840	3800	3840	3800	3840	3800

Standard errors in parentheses. Estimation by multilevel mixed-effects logistic regression with hierarchical clustering on group and subject level. *, ** and *** denote significance at the 10 %, 5 % and 1 % level, respectively.

Table 1.B.3: Interaction between privacy concern, learning and location.

Chapter 2

Adoption of Teamwork in Knowledge-intensive Production

2.1 Introduction[54]

Over the past decades, teamwork has become an integral part of work processes in organizations. Lawler et al. (2001) show that the share in Fortune 1,000 firms with more than 20 % of their employees in teams rose from 37 % in 1987 to 66 % in 1996. More recently, in a global survey among leaders of organizations, 31 % of the surveyed reported that most of the work in their organization is done in teams (Deloitte, 2019). One explanation why teamwork plays such a crucial role in organizations is that it can improve the productivity of workers (Hamilton et al., 2003) by combining workers' complementary skills (Lazear and Shaw, 2007). Therefore, workers' knowledge and skills become more important with teamwork. The importance of their knowledge for organizations is also highlighted by the increased implementation of human resource practices such as multi-tasking, job rotation and hiring highly-skilled workers (Caroli and Van Reenen, 2001, Ichniowski et al., 1997).

Empirical studies show that teamwork is favorable in complex production environments, i.e., knowledge is important (Boning et al., 2007, Cooper and Kagel, 2005). Furthermore, team performance in complex production environments can be improved by endowing teams with decision-making authority (Cordery et al., 2010, Haas, 2010, Rousseau and Aubé, 2010). Such self-managed teams can often decide on performance goals, task assignment and schedules, as well as team composition (Hollenbeck et al., 2012, Magpili and Pazos, 2018).

The purpose of this chapter is to help understand under which conditions organizations engaged in knowledge-intensive production adopt teamwork. Absent any incentive issues, we study the coordination problems of an organization presented with the choice to implement teamwork from a theoretical point of view. Furthermore, we help understand when an organizational designer implements self-managed teams.

We develop a model of a knowledge-intensive organization where production takes place in form of problem solving. Workers are endowed with knowledge profiles determining their ability to solve problems. We assume that problem types, which we define as the knowledge needed to solve a problem, are unknown ex ante. An organizational designer hires workers based on their knowledge profiles and decides on the organizational structure, i.e., how much time workers spend producing individually and in teams. When they work individually they can only rely on their own knowledge to solve a problem. Workers in teams can communicate and help each other by exchanging knowledge. Therefore, as a team, workers can use each others' knowledge to solve problems. We assume that knowledge transfer is not perfect.

There are different explanations for why knowledge cannot be perfectly transferred. Nonaka (1994) categorizes knowledge into tacit and explicit knowledge. While explicit knowledge is tangible and can easily be transferred, tacit knowledge is based on

[54]This chapter is joined work with Anja Schöttner. We thank participants at the Annual Conference of the TRR 266 in Mannheim, and LEOH 2019 in Berlin as well as participants in seminars in Berlin and Munich. I acknowledge financial support by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation), Project-ID 403041268-TRR 266.

learning from experience and is connected to a person. It can, therefore, not be transferred as easily. An empirical study by Hollenbeck et al. (2004) shows that some overlap in workers' skills makes communication more effective. This implies that agents with similar knowledge profiles can share knowledge more easily. We take this into account with frictions in knowledge transfer[55] that depend on workers' knowledge profiles. For the organizational designer there is a three-way trade-off between the degree of specialization in knowledge, frictions in knowledge transfer and the production design. The more overlap there is in workers' knowledge, the smaller are the transfer frictions. However, the more similar workers' knowledge is the less they can benefit from exchanging knowledge (Hollenbeck et al., 2004). Therefore, relying on an individual's knowledge to solve a problem can be better than to work in a team. Since transferring knowledge is costly, the organizational designer must assess when it is optimal to work in teams.

We can describe the optimal organization as follows. In terms of knowledge profiles, we find that under pure individual production, the organizational designer hires workers with identical knowledge profiles. Optimal knowledge profiles depend on the degree of problem uncertainty such that a decrease in problem uncertainty leads to workers being more specialized in the relevant knowledge dimension. Under pure teamwork, a certain degree of differentiation in workers' knowledge profiles is optimal. Workers can benefit from the differentiation because they can learn from knowledge transfers. However, since we assume that transfer frictions depend on the degree of specialization, it is optimal when workers' knowledge profiles span both dimensions.

In terms of organizational design, we observe that the organization is optimally either involved in pure teamwork or pure individual work. Pure teamwork is optimal if knowledge spillovers are sufficiently high. High knowledge spillovers imply that knowledge transfers between team members go both ways, thus communication is more effective. When spillovers are below the threshold, individual production is optimal as communication between workers is not worthwhile. Given that pure teamwork is optimal and problem types are uncertain, the organizational designer directs the communication within the team and decides which problem workers talk about. Thus, the team is management-led. Generally, the designer decides that the worker whose knowledge is more likely to be relevant learns from their co-worker. However, when spillovers are perfect or problem types are equally likely, i.e., problem uncertainty is very high, the organizational designer gives the team decision-making authority over the communication process. That means, the team members themselves can decide which problem they talk about. We refer to this as a self-managed team. Self-managed teams are weakly optimal in our model and arise endogenously. We can also determine the optimal organizational design in terms of the interaction between problem uncertainty and spillovers. The expected

[55] We refer to these as transfer frictions.

output from teamwork is linearly increasing in a lower problem uncertainty, whereas the expected output from individual production is convexly increasing in a lower problem uncertainty. We find that when spillovers are sufficiently high, teamwork is optimal for a sufficiently high problem uncertainty. When spillovers are only at an intermediate level, teamwork is optimal only for an intermediate problem uncertainty but not for a high problem uncertainty. Under teamwork some of the marginal cost from an increased uncertainty can be compensated with higher knowledge spillovers. Higher knowledge spillovers imply that even the worker who is not working on their own problem but helping their co-worker has a higher likelihood of solving their own problem.

2.1.1 Related Literature

This chapter is related to the literature on team theory that focuses on coordination, communication and specialization of workers in organizations. Bolton and Dewatripont (1994) depict the organization of firms as a communication network of workers who process a steady flow of information. Workers' specialization can increase productivity. However, more specialization needs more communication within the organization. Therefore, efficient networks are centralized and pyramidal to avoid duplication of communication. Becker and Murphy (1992) study a similar trade-off. Workers can increase productivity by focusing on different tasks, however, coordinating specialized workers is costly. Thus, specialization is limited by coordination costs. Common to both articles is the idea that workers need to combine their tasks or information to produce an output, thus, they engage in teamwork. In an empirical study, Hamilton et al. (2003) demonstrate that the introduction of teamwork in a garment factory increased productivity by 14 % and explain the result with the use of complementary skills in teams.

Becker and Murphy (1992) as well asBolton and Dewatripont (1994) both recognize costs of communication and coordination as limits to specialization. In a more recent article by Dessein and Santos (2006), the authors study the effect of improvements in modern communication technology on workers' specialization. The above articles predict that improving communication leads to more specialization. Dessein and Santos (2006), however, take into account that organizations can also choose the degree to which they adapt to local information. Adaptive organizations reduce coordination costs by limiting specialization. Therefore, improving communication on the one hand favors adaptive organizations and reduces specialization, but on the other hand it reduces the cost of coordinating and leads to more specialization. The former effect can also account for the observed transformation in organizations towards more teamwork, multi-tasking and empowering employees (Caroli and Van Reenen, 2001).

Garicano (2000) takes a different perspective on the organization of production in an organization. He views knowledge as the central ingredient to production and identifies acquisition, communication and use of knowledge as the coordination problems that arise in organizations. The coordination problems emerge because knowledge is dispersed among workers who face a time constraint. In his model, an organization optimally takes the form of a knowledge-based hierarchy. That is, workers on the production floor try to solve problems and ask managers in the next layer for help if they cannot solve a problem. Agents in each hierarchy layer have the same knowledge and knowledge is ranked by complexity.

This chapter is part of the literature on team theory as we also focus on coordination problems in organizations that arise from specialization and communication. However, we focus on the coordination problems connected to choosing between teamwork or individual production. We look at communication in terms of helping team members and specialization in terms of knowledge acquisition as in Garicano (2000).

There is a vast literature that studies teamwork and team incentives. Holmstrom and Milgrom (1990) investigate under which conditions a principal wants to compensate agents as team. They find that even when two agents perform technologically independent tasks, team compensation can be optimal. It is optimal when agents are risk averse and face negatively correlated risks. If risks are interdependent each agent's output signal contains information about the other agent as well. According to the informativeness principle this information should be used in compensation schemes to reduce the risk premium paid to the agents. Itoh (1992) researches in a similar vein. He asks under which conditions a principal wants to induce cooperation among groups of agents. In his model, there are two agents who each exert effort in the same two tasks. This way the agents can act as team. He shows that if agents are compensated as a team the principal benefits from side-contracting of agents. Due to the agents monitoring activity, the principal can induce the same effort levels while paying a lower risk premium. Che and Yoo (2001) study the effect of repeated interaction on incentives for teams. They find that repeated interaction between agents leads to peer pressure with a feasible punishment strategy. That way implicit incentives for agents increase and the principal can reduce explicit incentives. All these articles offer incentive-driven explanations for when organizations implement teamwork. In this chapter, we offer an explanation based on an organization's coordination problems.

Researchers in the management and organization literature realized the importance of SMTs and investigated research questions such as: How can managers effectively implement SMTs? What makes SMTs successful (Elmuti, 1997, Langfred, 2007, Magpili and Pazos, 2018, Wageman, 1997, 2001)? Despite the high practical relevance of SMTs, the economic perspective on SMTs is still underdeveloped. Kräkel (2017) looks at SMTs that have authority to decide on team composition. In his model, workers decide whether they want to work in a homogeneous or heterogeneous team. Since workers have better information about which match is efficient, the firm delegates the decision to make use of the decentralized information. However, workers can use this authority to engage in mismatching in order to influence the incentive pay. Adrian and Möller (2020) focus on incentives for self-managed teams and research the effect of pay dispersion on the performance of self-managed teams. The authors show that pay dispersion has a positive effect on team effort, but a negative effect on information sharing within the team. Hence, the optimal incentives for information sharing are diametrically opposed to the optimal incentives for effort exertion. The economic literature on SMTs focuses on incentive problems. We contribute to this literature by helping to understand under which conditions an organization chooses to implement SMTs without taking the effects of incentives into account.

This chapter is organized as follows: In Section 2.2, we develop the model set-up. After that, in Section 2.3, we analyze the model with respect to workers' knowledge profiles and organizational design. Section 2.4 presents an extension of the baseline model. Finally, Section 2.5 discusses and summarizes the results.

2.2 Model

In this section, we first explain the basic assumptions and set-up of the model. Afterwards we focus on the setting of pure individual production and pure team production, respectively.

2.2.1 Basic Set-up

We analyze the optimal design of an organization with two workers, A and B. The workers produce by solving problems. Worker A and worker B each have one unit of time to try and solve a problem that they draw from a commonly known distribution. A problem that is successfully solved gives the organization an output of one. An unsolved problem yields an output of zero. Since we do not consider contracting in this setting, the wage for workers is normalized to zero.

Workers need to have knowledge in order to solve problems. Knowledge has two dimensions, dimension 1 and dimension 2. Worker A's and worker B's knowledge profiles are denoted $\boldsymbol{a} = (a_1, a_2)$ and $\boldsymbol{b} = (b_1, b_2)$, respectively. Thus, a worker's knowledge in dimension 1 and 2 is represented by i_1 and i_2, respectively, for $i = a, b$. Knowledge is non-negative, $i_1, i_2 \geq 0$. We assume that a worker's knowledge profile corresponds to one specific point on a "quarter" circle with radius one in a two-dimensional space reflecting the knowledge dimensions, i.e., $i_1^2 + i_2^2 = 1$ (cf. Figure 2.1). Hence, we can express workers' knowledge in dimension 2 in terms of dimension 1, since $i_2 = \sqrt{1 - i_1^2}$. We drop subscripts whenever this is possible without causing confusion and write $a_1 = a$ and $b_1 = b$. The organizational designer chooses knowledge profiles by hiring workers with the respective knowledge. All knowledge profiles with $i_1^2 + i_2^2 = 1$ and $i_1, i_2 \geq 0$ are available on the labor market. Without loss of generality, we assume that $a \geq b$, such that worker A is weakly more knowledgeable

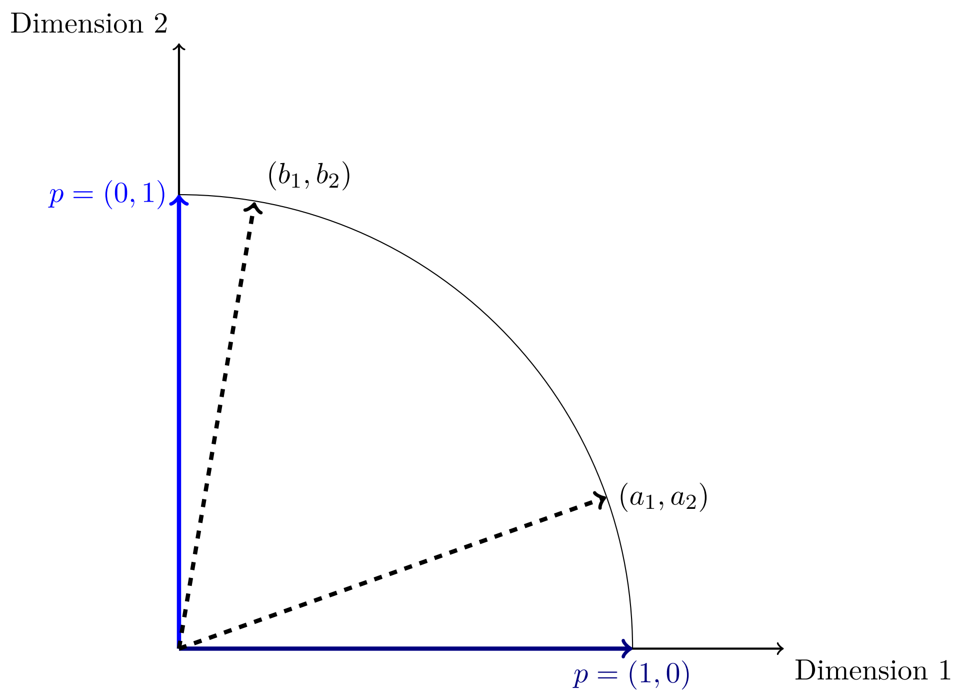


Figure 2.1: Problem types and exemplary knowledge profiles for A and B

in dimension 1 than worker B, whereas worker B is weakly more knowledgeable in dimension 2.

A problem is characterized by the combination of knowledge that is required to solve it with certainty, i.e., $\boldsymbol{p} = (p_1, p_2)$, with $p_1, p_2 \geq 0$ and $p_1^2 + p_2^2 = 1$. Dimension 1 of a problem, p_1, is the realization of a random variable that is distributed according to the cdf $H(\cdot)$, and p_2 is given by $p_2 = \sqrt{1 - p_1^2}$. We call $\boldsymbol{p}$ the problem's type and assume that $\boldsymbol{p}$ is not observable. This assumption indicates that problems are novel, non-routine issues. It is unclear how they can be solved and what knowledge is required to solve them until a solution is found. This also implies that it is not sensible to let workers switch their problems, since they do not know ex ante what knowledge they need in order to solve it. In the baseline model, we restrict our attention to two different problems that workers can encounter. Either a problem is of type $\boldsymbol{p} = (1, 0)$ or of type $\boldsymbol{p} = (0, 1)$.[56] Accordingly, for each given problem, one can find a solution by applying only knowledge from one of the dimensions. However, which dimension is crucial to solve a problem is only revealed when a solution is found. The probability function of the problem types is given by $\Pr[p_1 = 1] = r$ and $\Pr[p_1 = 0] = 1 - r$ with $r \in [0, 1]$. Without loss of generality, we assume $r \geq \frac{1}{2}$, i.e., problems requiring knowledge in dimension 1 are relatively more likely to occur. Figure 2.1 illustrates our assumptions on knowledge profiles and problem types graphically. The dashed vectors display possible knowledge profiles of workers A and

[56] As this chapter is a work in progress, we make this assumption to simplify the analysis for some first results. In Section 2.4, we extend the model to three different problems.

B along the unit circle. The light and dark blue vectors give the positioning of the problems we restrict our attention to in the baseline model of this chapter.

As an example for such a situation, take the setting that Cordery et al. (2010) study in a field experiment, namely problem solving in wastewater plants. In simplified terms, the goal of any wastewater plant is to emit water that conforms to a certain quality standard. This goal can be reached either through biological or chemical processes. If a worker observes that the water quality is below the acceptable level, it can either be a problem due to miscalculation of chemicals or due to an error in the biological process. Only by successfully rectifying the problem, can the worker find out whether it was a chemical or a biological issue. This reflects the kind of problems we have in mind for this model: Non-routine tasks that are solved through trial-and-error.

The organizational designer decides to what extent workers engage in teamwork or individual work. Particularly, they choose how much time each worker spends working alone, helping their colleague or learning from their colleague. Let t_j^w denote the time worker j ($j = A, B$) spends working individually on a problem, t_j^h denotes the time worker j helps their colleague with the colleague's problem, and t_j^l the time worker j receives help (learns) from their colleague. The time budget constraint states that $t_j^w + t_j^h + t_j^l = 1$, since each worker has one time unit to solve a problem.

2.2.2 Individual Production

We first describe the problem-solving process for the case of *pure individual work*, i.e., $t_A^w = t_B^w = 1$. If each worker works only individually on a problem that they drew, then the problem is solved with probability $i_1 p_1 + i_2 p_2$ for $i = a, b$. When we look at Figure 2.1 this means the larger the angle between, e.g., vectors $\boldsymbol{a}$ and $\boldsymbol{p} = (1, 0)$, the less likely worker A is to solve this type of problem. A problem $\boldsymbol{p}$ will be solved with certainty if and only if the worker's knowledge profile perfectly matches the problem, i.e., $i_1 = p_1$ and $i_2 = p_2$. In the opposite extreme, if the worker is fully specialized in one dimension, say dimension 1 (i.e., $a = 1$), but the problem requires maximum knowledge in dimension 2 (i.e., $\boldsymbol{p} = (0, 1)$), the problem cannot be solved with pure individual work. Accordingly, under pure individual work worker A's and worker B's expected output as a function of their knowledge is

$$Q_A(a) := ra + (1 - r)\sqrt{1 - a^2},$$
$$Q_B(b) := rb + (1 - r)\sqrt{1 - b^2},$$

respectively. With probability r, a problem that requires specialization in dimension 1 is drawn, i.e., $\boldsymbol{p} = (1, 0)$. Then, only the workers' knowledge in dimension 1 is relevant to solve that problem. With probability $1 - r$, a problem that requires specialization in dimension 2, i.e., $\boldsymbol{p} = (0, 1)$, is drawn. Then, only knowledge in dimension 2 defines the probability of solving that problem.

2.2.3 Team Production

When workers deal with a problem as a team, still each worker draws a problem, but they can communicate about how to solve the problems. By communicating, workers can learn from each other through knowledge transfers. However, they can only work on one problem at a time. This means that they talk either about A's or B's problem. In the former case, we say that A receives help or learns from B. In the latter case, the opposite applies. In terms of the organizational designer's choice on time allocation, this means $t^h_j = t^l_k$, and $t^w_j = t^w_k := t^w$ for $j,k = A,B$ and $j \neq k$. Therefore, it suffices to concentrate on the time allocation for t^w, t^h_A and t^l_A.[57]

We proceed with explaining the problem-solving process under *pure teamwork*, i.e., $t^w = 0$ and thus $t^h_A + t^l_A = 1$. If the workers talk only about A's problem, i.e., $t^l_A = 1$, worker A's expected output is

$$Q^T_A(a,b) := ra + (1-r)(\sqrt{1-b^2} - K(a,b)).$$

Similarly, if $t^h_A = 1$ so that A helps B all the time, worker B's expected output is given by

$$Q^T_B(a,b) := r(a - K(a,b)) + (1-r)\sqrt{1-b^2}.$$

To understand these functions, consider worker A. If worker A encounters a problem $\boldsymbol{p} = (1,0)$, their own knowledge in dimension 1 determines the success probability, since we assume without loss of generality that A is weakly more knowledgeable in dimension 1 than B. This determines the first term of A's expected output. In contrast, if A encounters a problem $\boldsymbol{p} = (0,1)$, their colleague's knowledge in dimension 2 determines the success probability, since B is weakly more knowledgeable in dimension 2 than A. However, the knowledge available from B is reduced by a friction occurring in the knowledge transfer, $K(a,b)$. This defines the second term of A's expected output. The same holds for the expected output of worker B.

We assume that knowledge transfers are not perfect and workers with similar knowledge profiles can share knowledge more easily, as we already discussed in the introduction (Nonaka, 1994, Hollenbeck et al., 2004, Dessein and Santos, 2006). The function $K(a,b) \geq 0$ describes these frictions in knowledge transfer where $K(a,b)$ is increasing in the angle between the vectors (a_1,a_2) and (b_1,b_2). We assume that $K(\cdot)$ is a strictly convex function. Moreover, $K(a,a) = 0$ for all a, i.e., if workers have identical knowledge profiles and thus there is no scope for knowledge transfer, there are no frictions either. Additionally, $K_a(a,a) = K_b(a,a) = 0$ for all a, i.e., starting from an identical background and then specializing just a little bit does not entail transfer frictions either. We exclude "de-learning", meaning that knowledge transfer will not reduce a worker's knowledge, that is $a - K(a,b) \geq b$ and $\sqrt{1-b^2} - K(a,b) \geq \sqrt{1-a^2}$ for all a,b with $a \geq b$. A function that fulfills all of

[57] We could eliminate one more time allocation variable by using $t^w + t^h_A + t^l_A = 1$, but decided to keep all three variables as we believe this is more instructive.

these characteristics is

$$K(a,b) = 1 - ab - \sqrt{1-a^2}\sqrt{1-b^2} = 1 - \cos(\theta),$$

where θ denotes the angle between the knowledge profiles (a_1, a_2) and (b_1, b_2).

Finally, we assume that while helping their colleague, a worker may also learn something that is helpful to solve their own problem. The parameter $s \in [0,1]$ indicates the strength of such knowledge spillovers. Consider worker B's expected output when $t^l_A = 1$. That is, we are looking at the expected output of B when their time is fully allocated to help A. Since we assume that the communication and learning process goes both ways via a parameter for spillovers s, worker B's productivity is sQ^T_B if $t^l_A = 1$. Similarly, if $t^h_A = 1$ such that A helps B all the time, worker A's expected output is sQ^T_A.

Overall, the total expected output of the organization is given by

$$\begin{aligned} Q(a,b,t^w,t^l_A,t^h_A) := {} & t^w(Q_A(a) + Q_B(b)) + (t^l_A + st^h_A)Q^T_A(a,b) \\ & + (t^h_A + st^l_A)Q^T_B(a,b). \end{aligned} \tag{2.1}$$

The first term of the equation gives the expected output from individual work, taking into account the time allocated to individual work. The second and third term represent the expected output from teamwork. Recall that Q^T_A is A's expected output when workers talk only about A's problem ($t^l_A = 1$). The term is weighted with the time A learns (t^l_A) and the time A helps but can learn through spillovers from B (st^h_A). It is analogous for B.

The timing is as follows:

1. The organizational designer chooses knowledge profiles a, b and the organizational design, i.e., t^w, t^h_A, and t^l_A in order to maximize the total expected output of the organization.

2. Each worker draws a problem.

3. Workers try to solve the problems, allocating their time between individual production and team production as stipulated by t^w, t^l_A, and t^h_A.

4. Outcomes are observed, i.e., whether a worker's problem has been solved or not.

2.3 Analysis

In the analysis of the model, we first derive the optimal knowledge profiles of workers under pure individual production (i.e., $t^w = 1$) and pure team production (i.e., $t^w = 0$), respectively. In a second step, we analyze the optimal organizational design, i.e., we study the optimal time allocation for t^w, t^h_A, and t^l_A.

2.3.1 Knowledge Profiles under Individual Production

Let us first look at knowledge profiles under pure individual production. That means we take $t^w = 1$ as given for this section, so that no communication is allowed. Each worker draws a problem and tries to solve it alone. The organizational designer hires workers with knowledge profiles that maximize the organization's total expected output given that $t^w = 1$. That is, they choose a and b to solve $\max_{a,b} Q_A(a) + Q_B(b)$.

Lemma 2.1 *Under pure individual production, $t^w = 1$, the organizational designer hires workers A and B with identical knowledge profiles such that*

$$a^I = b^I := \frac{r}{\sqrt{1 - 2r(1 - r)}}.$$

Proof. *See Appendix.* ■

In Lemma 2.1, the optimal knowledge in dimension 1 is increasing in r. The larger r, i.e., the more likely a problem of type $\boldsymbol{p} = (1, 0)$ is, the more specialized are workers in dimension 1. Workers then have a higher chance of solving a problem they draw. If $r > 1/2$, then $a^I > \sqrt{1 - (a^I)^2}$, implying that workers have more knowledge in dimension 1 than in dimension 2. If $r = 1/2$, i.e., both problems are equally likely, then $a^I = 1/\sqrt{2}$. That is, workers are not specialized in one of the dimensions, but rather equally knowledgeable in each dimension. The vector of the knowledge profile, (a_1^I, a_2^I), corresponds to the 45-degree line. On the other hand, if $r = 1$, meaning it is certain ex ante that a problem of type $\boldsymbol{p} = (1, 0)$ arises, workers are fully specialized in dimension 1. Notice that this is the only situation under individual production where workers are fully specialized.

2.3.2 Knowledge Profiles under Team Production

We now turn to a situation where workers can communicate to solve their problems. Particularly, we investigate pure team production and thus take $t^w = 0$ as given, which implies that $t_A^h + t_A^l = 1$ due to the time budget constraint. Moreover, in this section, we also take t_A^h as given, which then determines t_A^l and thus characterizes the optimal knowledge profiles for a given allocation of helping and learning time under pure team production. Recall that under pure teamwork if A gets help from B for the whole time unit, i.e., $t_A^l = 1$, worker A's expected productivity is

$$Q_A^T(a, b) := ra + (1 - r)(\sqrt{1 - b^2} - K(a, b)).$$

Similarly, if $t_A^h = 1$ so that A helps B all the time, worker B's expected productivity is given by

$$Q_B^T(a, b) := r(a - K(a, b)) + (1 - r)\sqrt{1 - b^2}.$$

The expected output of the organization under pure teamwork can be written as

$$\begin{aligned} Q^T(a,b) &= (t_A^l + s t_A^h) Q_A^T(a,b) + (t_A^h + s t_A^l) Q_B^T(a,b) \\ &= (1+s)\bar{Q}^T(a,b) - \left[(1-r)(t_A^l + s t_A^h) + r(t_A^h + s t_A^l)\right] K(a,b), \end{aligned} \tag{2.2}$$

where $\bar{Q}^T(a,b) := ra + (1-r)\sqrt{1-b^2}$ denotes the expected output under pure team production in the absence of transfer frictions, i.e., if we had $K(a,b) = 0$ for all a, b.

To determine the optimal knowledge profiles of workers A and B for fixed t_A^h and t_A^l under pure teamwork, the organizational designer's objective is to maximize equation (2.2) with respect to a and b while taking t_A^l and t_A^h as given.

Lemma 2.2 *Consider pure teamwork, $t_A^h + t_A^l = 1$, for a fixed t_A^h. Let a^T and b^T denote the optimal knowledge in dimension 1 of worker A and B, respectively. For $r = 1$, the workers' optimal knowledge profiles are identical and we obtain $a^T = b^T = 1$. For $r \in [1/2, 1)$, we obtain $a^T > b^T$, i.e., the workers' knowledge profiles differ.*

Proof. *See Appendix.* ■

Lemma 2.2 shows that when the nature of the problem is uncertain (i.e., $r < 1$), the optimal knowledge profiles under teamwork differ, which is in contrast to the identical knowledge profiles under individual production. The organizational designer chooses workers with heterogeneous knowledge profiles for teams, so workers can benefit from communication and the expected output of the team increases compared to a situation with identical knowledge profiles. To obtain this result, our assumption $K_a(a,a) = K_b(b,b) = 0$ is important as it implies that frictions in knowledge transfers are negligible when workers specialize a bit more starting from identical knowledge profiles. This makes at least some specialization beneficial for an organization that implements teamwork. Moreover, our assumption that knowledge transfer is less effective the more workers' knowledge profiles differ implies that workers' knowledge should in general comprise both knowledge dimensions, i.e., $a^T < 1$ and $b^T > 0$.

For the special case of $r = 1$ where it is ex ante certain that problem type $\boldsymbol{p} = (1,0)$ is encountered, it is optimal for the organizational designer to hire workers with identical fully specialized knowledge profiles. Both workers are experts in the required knowledge dimension 1, such that $a = b = 1$. In that case, there is no benefit from communicating in a team.

2.3.3 Organizational Design

In this section we focus on the question, how the organizational designer structures the production by choosing t^w, t_A^h and t_A^l. First, note that we can rewrite the total expected output from equation (2.1) as follows:

$$Q(a,b,t^w,t_A^h,t_A^l) = t^w(Q_A(a) + Q_B(b)) + (t_A^l + t_A^h)(1+s)\bar{Q}^T(a,b)$$

$$
\begin{aligned}
&- \left[(1-r)(t_A^l + s t_A^h) + r(t_A^h + s t_A^l)\right] K(a,b) \\
=& t^w (Q_A(a) + Q_B(b)) + (1-t^w)(1+s)\bar{Q}^T(a,b) \\
&- \left[(1-r)(t_A^l + s t_A^h) + r(t_A^h + s t_A^l)\right] K(a,b).
\end{aligned}
$$

For the first equation we used the definition of $\bar{Q}^T$ (from Section 2.3.2), for the second equation we used the time budget constraint, $t^w + t_A^l + t_A^h = 1$.

We first consider the special case where the nature of the problem is certain ex ante, i.e., $r = 1$. Expected output then reduces to

$$
Q(a, b, t^w, t_A^h, t_A^l) = t^w(a+b) + (1-t^w)(1+s)a - (t_A^h + s t_A^l)K(a,b).
$$

It is then optimal to hire two workers with knowledge only in dimension 1, $a = b = 1$, and implement pure individual work, $t^w = 1$, because this leads to the maximum possible output of 2. When the nature of the problem is certain, there is no gain from hiring workers with different knowledge profiles and communication is even detrimental as the worker who helps their colleague cannot work on their own problem. Henceforth, we focus on situations where the nature of the problem is ex ante uncertain, $r \in [\frac{1}{2}, 1)$.

We now characterize the optimal organizational design depending on the extent of knowledge spillovers.

Proposition 2.1 *Suppose that the nature of the problems drawn by the workers is uncertain, i.e., $r \in [1/2, 1)$. There exists a threshold $\bar{s}(r) \in (0,1)$, such that pure individual work ($t^w = 1$) is optimal if $s \leq \bar{s}(r)$. Otherwise, pure teamwork ($t^w = 0$) is optimal and problem solving within the team is structured as follows:*

(i) If $s > \bar{s}(r)$ and $r > 1/2$, worker B always helps worker A with their problem, i.e., $t_A^h = 0$ and $t_A^l = 1$.

(ii) If $s > \bar{s}(r)$ and $r = 1/2$, the organizational designer does not need to impose any structure on the problem-solving process as any pair t_A^l, t_A^h with $t_A^l + t_A^h = 1$ is optimal.

(iii) If $s = 1$, again any pair of t_A^l, t_A^h with $t_A^l + t_A^h = 1$ is optimal. That is, the optimal design does not depend on r.

Proof. *See Appendix.* ■

In Proposition 2.1, we look at the organizational designer's optimal choices for t^w, t_A^h and t_A^l when problems are ex ante uncertain. We find that the optimal choice of t^w is a corner solution. The total expected output is linear in t^w for all $r \in [\frac{1}{2}, 1)$ so that it is optimal to choose $t^w \in \{0, 1\}$. In our model, the unit of time workers are given to solve a problem is valued uniformly. Choosing an organizational design where workers, for example, first engage in individual production and towards the end of their time unit get involved in team production cannot be optimal in our model.

Pure individual work is implemented when knowledge spillovers are below the threshold $\bar{s}(r)$. Pure teamwork is implemented when spillovers are sufficiently high. When spillovers are high, communication between co-workers is more efficient because not only the expected output of the team member who learns increases, but also the expected output of the co-workers who helps.

In the second part of Proposition 2.1, we focus on the designer's choice of t_A^h and t_A^l which determines the communication process in the team. Given that spillovers are above the threshold $\bar{s}(r)$ so that pure teamwork is optimal, it is optimal to set $t_A^h = 0$ and $t_A^l = 1$ if $r > \frac{1}{2}$. Intuitively, as a problem of type $\boldsymbol{p} = (1, 0)$ is more likely to be drawn, worker A's specialization is more likely to be useful than B's to solve the problem since $a \geq b$. Hence, A's expected output under teamwork is larger than B's, because B encounters transfer frictions in dimension 1 which is more likely to be relevant. To minimize the cost from transfer frictions, the organizational designer decides that worker B must learn via spillovers from A rather than facing full transfer frictions from A helping B directly. Workers focus on A's problem because A is more likely to solve a problem. B can learn from spillovers in dimension 1.

Overall, the organizational designer decides that the worker whose knowledge is more likely to be relevant spends all their time learning. We call this team a *management-led team*, since the organizational designer directs the rules for communication ex ante and decides which problem a team talks about.

On the other hand, when both problem types are equally likely ($r = \frac{1}{2}$) or when spillovers are perfect ($s = 1$) the designer can let the team decide on values for t_A^h and t_A^l. We refer to this as a *self-managed team* because the team can decide on their own how to allocate their time and thus the team shapes the communication process. A self-managed team arises endogenously in our model as a corner solution to the organizational designer's problem to determine the organization's optimal structure. However, a self-managed team is just weakly optimal as it leads to exactly the same output as a management-led team.

2.3.4 Organizational Design and Problem Uncertainty

In this section, we discuss how the optimal organizational design depends on the degree of problem uncertainty, which is described by the parameter r in our model.

In Lemma 2.1, we solved for the optimal knowledge profiles, a^I, under individual production. The corresponding expected total output is given by

$$Q^I(r) := 2\sqrt{1 - 2r(1-r)},$$

which is strictly increasing and strictly convex in r. Intuitively, if it is more likely that a problem of type $\boldsymbol{p} = (1, 0)$ is drawn, the organization can safely hire workers that are more specialized in dimension 1 and therefore more likely to solve their problems. This increases the expected output. Hence, pure individual work is more effective the more precise the ex-ante knowledge of the type of problem workers are going to face. When $r = 1$, as we showed in Section 2.3.2, it is optimal for the organizational designer to hire workers who are specialized in dimension 1 such that $a = b = 1$. Each worker is able to solve their problem on their own with certainty and $Q^I(1) = 2$, which is the maximum feasible output.

For teamwork, the analysis is not as simple as optimal knowledge profiles and consequently output depends on the specific functional form of $K(a, b)$. In Lemma 2.2, we established that knowledge profiles under teamwork are optimally differentiated. However, we cannot determine the optimal knowledge profiles as functions of r. Therefore, to simplify the analysis, we assume in this section that transfer frictions are independent of a and b such that $K(a, b) = \bar{K}$ for all $a \neq b$ with $\bar{K} \in (0, 1)$. In such a situation, there is no benefit from hiring workers that are less than fully specialized, since the effectiveness of knowledge transfers does not decrease with the workers' specialization. The optimal choice of the organizational designer is to hire worker A as an expert in dimension 1, $a^T = 1$, and worker B as an expert in dimension 2, $b^T = 0$. Notice that this is in contrast to what we find when transfer frictions are not fixed. In that case, workers' knowledge usually comprise both knowledge dimensions, because we assume that transfers are less effective the more workers' knowledge profiles differ.

We can show that for sufficiently high spillovers, the results from Proposition 2.1 qualitatively extend to the case of fixed transfer frictions.[58] By substituting workers' fully specialized knowledge profiles into the overall expected output in equation (2.1) and applying the results from Proposition 2.1, the expected output for teamwork as a function of r is

$$Q^T(r) = 1 + s - (1 - r(1 - s))\bar{K}.$$

The expected team output is linearly increasing in r. Because knowledge profiles are fully specialized, r affects the expected team output only through the probability with which transfer frictions arise. The more certain a problem of type $\boldsymbol{p} = (1, 0)$ becomes, the more relevant is knowledge in dimension 1. Since worker A is fully specialized in dimension 1, A's knowledge is more relevant. To minimize the cost from transfer frictions, it is optimal that worker B helps A, as we developed in Proposition 2.1. This implies that transfer frictions reduce expected team output less the higher r because frictions arise from B learning via spillovers from A.

The expected team output reaches its maximum at $r = 1$. However, as we determined above, for $r = 1$ it is optimal to hire workers who are both specialized in dimension 1. Since workers cannot transfer knowledge, communication is harmful. Therefore, the expected output from teamwork under certainty is always below the optimal output from individual production.

[58] For $s > \frac{2\sqrt{1-2r(1-r)}+(1-r)\bar{K}-1}{1-r\bar{K}}$, it is optimal to choose teamwork over individual work when transfer frictions are fixed.

Proposition 2.2 *Suppose that frictions in knowledge transfer are such that $K(a,b) = \bar{K} > 0$ for all $a \neq b$. We can distinguish three cases:*

(i) If s is sufficiently small, pure individual work is optimal.

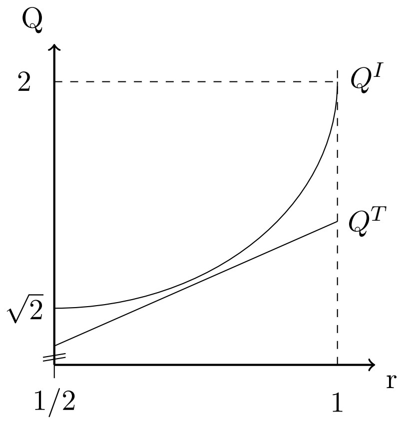
(ii) If s takes intermediate values, pure individual work is optimal for sufficiently small and sufficiently high r. For intermediate r, pure teamwork is optimal.

(iii) If s is sufficiently high (i.e., $s \geq \frac{\sqrt{2}}{1-K/2} - 1$), there exists a threshold $\bar{r} \in (\frac{1}{2}, 1)$ such that pure individual work is optimal if and only if $r > \bar{r}$ and pure teamwork is optimal otherwise.

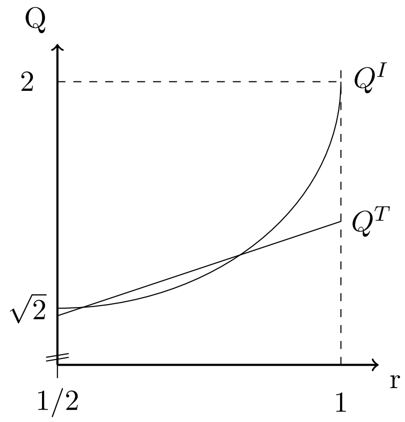
Proof. *See Appendix.* ■

The results presented in Proposition 2.2 are driven by the fact that with fixed frictions in knowledge transfer, the optimal knowledge profiles under teamwork are independent of r. Workers are fully specialized so that, ignoring frictions in knowledge transfer, their expected output is also independent of r. If $\bar{K}$ was zero, two fully specialized workers engaging in teamwork would solve worker A's problem with certainty, while the chance of solving worker B's problem depends on knowledge spillovers ($(1+s)\bar{Q}^T(1,0) = 1+s$). Thus, with $\bar{K} > 0$, changes in r only affect the probability with which frictions in knowledge transfer occur. The lower the degree of uncertainty, the smaller the probability with which transfer frictions arise. As a consequence, the marginal benefit from a reduced problem uncertainty is constant under teamwork, i.e., $Q^T(r)$ is linearly increasing in r. We can see from Proposition 2.2 that there is an interaction between s and r in the expected output from teamwork. When the probability of solving B's problem is high enough, it can compensate the probability with which transfer frictions arise, so that teamwork dominates individual production for certain r (cases (ii) and (iii) of Proposition 2.2). By contrast, under individual production the marginal benefit from a reduced problem uncertainty is increasing, i.e., $Q^I(r)$ is convexly increasing in r. A decrease in uncertainty implies that workers' knowledge profiles can be specialized more in the dimension that is more likely to be relevant. The higher degree of workers' specialization complements the higher chance of being able to solve a problem. The effect is stronger the higher r.

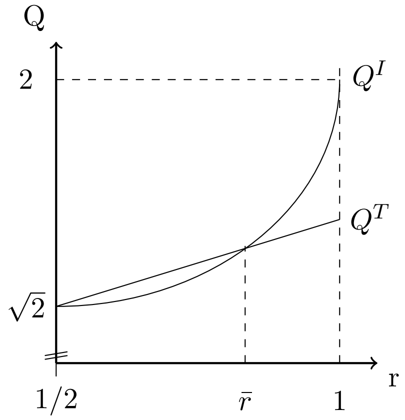
Figure 2.2 outlines the results of Proposition 2.2 graphically. The graphs depict Q^T as a linear function of r and Q^I as a convex function of r. For sufficiently small spillovers (cf. Figure 2.2a), teamwork is dominated by individual production for all $r \in [\frac{1}{2}, 1]$. This result also holds for non-fixed transfer frictions, $K(a,b)$, as described in Proposition 2.1. For intermediate spillovers (cf. Figure 2.2b), teamwork dominates individual work for intermediate values of r. For sufficiently high spillovers (cf Figure 2.2c), teamwork dominates individual work as long as problem uncertainty is below the threshold $\bar{r}$.



(a) Case (i) of Proposition 2.2



(b) Case (ii) of Proposition 2.2



(c) Case (iii) of Proposition 2.2

Figure 2.2: Graphic outline of Proposition 2.2

2.4 Organization with Three Problems

In this section, we extend the baseline model to include a third problem, thus increasing the degree of uncertainty. The two workers each draw a problem from the set of three problem types: $\boldsymbol{p} = (1, 0)$, $\boldsymbol{p} = (0, 1)$ and $\boldsymbol{p} = (\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}})$. The last problem requires that workers are equally knowledgeable in both dimensions. The problems are drawn according to the following probability distribution: $\Pr[p_1 = 1] = r$, $\Pr[p_1 = 0] = q$ and $\Pr[p_1 = \frac{1}{\sqrt{2}}] = 1 - r - q$ with $r, q \in [0, 1]$ and $r + q \leq 1$. We keep all other assumptions from the baseline model, so that results are comparable.

In pure individual production, the expected productivity of a worker is now defined as

$$Q_P^j(i) := ri + q\sqrt{1 - i^2} + (1 - r - q)\frac{1}{\sqrt{2}}(i + \sqrt{1 - i^2}),$$

for all $i = a, b$ and $j = A, B$. This function is a basic extension of workers' expected output as described in Section 2.3.1. The last term adds the expected output from solving a problem of type $\boldsymbol{p} = (\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}})$ where workers use both knowledge dimensions.

Due to the third problem that now needs to be taken into account, the knowledge profiles of workers cannot be explicitly defined anymore. However, since the expected output is well-behaved, the knowledge profiles are implicitly determined by

$$\frac{i}{\sqrt{1-i^2}} = \frac{r + \frac{1}{\sqrt{2}}(1-r-q)}{q + \frac{1}{\sqrt{2}}(1-r-q)}. \tag{2.3}$$

The left-hand side expresses the ratio of knowledge in dimension 1 to knowledge in dimension 2. When i increases the left-hand side increases. The right-hand side is increasing in r and decreasing in q. That means if a problem of type $\boldsymbol{p} = (1, 0)$ is more likely, the right-hand side of (2.3) increases and hence the left-hand side must also increase. Thus, when a problem that requires knowledge in dimension 1 is more likely to arise, the knowledge profile becomes more specialized in dimension 1. Since workers' expected output functions are the same for all $j = A, B, C$, the organizational designer optimally chooses identical knowledge profiles. In that sense, they are not qualitatively different from the knowledge profiles derived in Lemma 2.1.

In pure teamwork, the maximum feasible expected output is given by

$$\bar{Q}_P^T(a, b) := ra + q\sqrt{1-b^2} + \frac{1}{\sqrt{2}}(1-r-q)(a + \sqrt{1-b^2}).$$

It reflects the fact that A is more knowledgeable in dimension 1 while B is more knowledgeable in dimension 2. We can use this function to define the expected team output of workers A and B as the maximal possible benefit from teamwork minus the cost from transfer frictions

$$\begin{aligned} Q_P^T(a, b) &:= (1+s)\bar{Q}_P^T(a, b) \\ &- \left[r(t_A^h + st_A^l) + q(t_A^l + st_A^h) + \frac{1}{\sqrt{2}}(1-r-q)(1+s)(1-t^w) \right] K(a, b). \end{aligned} \tag{2.4}$$

The last term in square brackets expresses the transfer frictions that emerge from talking about the new problem. Notice that this term is independent of time allocations t_A^h and t_A^l, because both workers can learn from each other in one dimension that is relevant to solving the problem. Equation (2.4) is not essentially different from (2.2) and (2.4) is also concave. Hence, we can follow the proof of Lemma 2.2 and show that optimal knowledge profiles under pure teamwork are heterogeneous even when there are three problem types. They are, therefore, also not qualitatively different from the optimal knowledge profiles of the baseline model. In the special case where a problem type is certain ex ante, optimally both workers' knowledge profiles are identical. As before, when a problem of type $\boldsymbol{p} = (1, 0)$ or $\boldsymbol{p} = (0, 1)$ is drawn with certainty, the knowledge profiles are specialized in the respective relevant dimension. However, if a problem of type $\boldsymbol{p} = (\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}})$ arises with certainty, both workers are equally knowledgeable in both dimensions.

Now, we turn to the optimal organizational design, i.e., the designer's choice of t^w, t^h_A and t^l_A. The overall expected output with three problem types is given by

$$Q_P(a,b) = t^w(Q^A_P(a) + Q^B_P(b)) + (1-t^w)(1+s)\bar{Q}^T_P(a,b)$$
$$- \left[r(t^h_A + st^l_A) + q(t^l_A + st^h_A) + \frac{1}{\sqrt{2}}(1-r-q)(1+s)(1-t^w)\right] K(a,b). \quad (2.5)$$

In the special cases where a problem type is certain ex ante and thus it is optimal to have workers who both have the relevant knowledge to solve the problem that is certainly drawn, communication is useless or even detrimental as a worker who helps their co-worker cannot work on their own problem. Therefore, we focus on situations where problem types are ex ante uncertain, i.e., $r, q \in (0,1)$.

Following Proposition 2.1, we can characterize the optimal organizational design with three problem types depending on knowledge spillovers.

Corollary 2.1 *Suppose problem types are uncertain, $r, q \in (0,1)$, there exist two thresholds $\bar{s}_P(r)$, $\bar{s}_P(q) \in (0,1)$. For $r > q$ pure individual work ($t^w = 1$) is optimal if $s \leq \bar{s}_P(r)$, while for $r < q$ pure individual work is optimal if $s \leq \bar{s}_P(q)$. Otherwise, pure teamwork ($t^w = 0$) is optimal. Problem solving within the team is structured as follows:*

(i) If $s > \bar{s}_P(r)$ and $r > q$, worker B always helps worker A with their problem, i.e., $t^h_A = 0$ and $t^l_A = 1$ is optimal.

(ii) If $s > \bar{s}_P(q)$ and $r < q$, worker A always helps worker B with their problem, i.e., $t^h_A = 1$ and $t^l_A = 0$ is optimal.

(iii) If $s > \bar{s}_P(q), \bar{s}_P(r)$ and $r = q = \frac{1}{3}$, the organizational designer does not need to impose any structure on problem-solving as any pair t^h_A, t^l_A that satisfies the time budget constraint is optimal.

(iv) If $s = 1$ for all $r, q \in (0,1)$, again any pair t^h_A, t^l_A is optimal.

Proof. *See Appendix.* ■

Corollary 2.1 closely resembles Proposition 2.1. Instead of one threshold for knowledge spillovers, however, there are two thresholds, $\bar{s}_P(r)$ and $\bar{s}_P(q)$, when there are three problem types involved. The additional problem that can be drawn in this situation requires both workers to be equally knowledgeable in both dimensions and does not affect the organizational designer's choice of t^h_A, t^l_A and t^w (cf. Equation (2.5)). Therefore, the results of the analysis are also not essentially different from the baseline model. It is still optimal to either choose pure individual work or pure team work. In the special cases where spillovers are perfect or where spillovers are sufficiently high and all problems are equally likely, the organizational designer still gives authority to the team to decide on t^h_A and t^l_A. On the other hand, if pure teamwork is optimal and a problem that requires specialization in dimension 1 is more likely, the designer decides that worker B always helps worker A who is more knowledgeable in the relevant dimension. Therefore, having a higher degree of uncertainty does not lead to qualitatively different results in the optimal organizational design compared to the baseline model. This is due to the fact that the additional problem in this section does not influence the organizational designer's choice of the time allocation.

2.5 Conclusion and Discussion

In this chapter, we develop a model of an organization which produces by solving problems. An organizational designer faces two coordination issues: hiring workers with optimal knowledge profiles and choosing the optimal organizational design with respect to allocation of workers' time.

In terms of workers' knowledge profiles, we observe that an organizational designer chooses different knowledge profiles depending on the organizational design. If workers engage in pure individual production, the organizational designer hires employees with identical knowledge profiles, because workers do not engage in knowledge transfer. Depending on the probability with which a specific problem type is drawn, workers are more specialized in one or the other dimension. However, if the designer chooses pure teamwork, the knowledge profiles of workers are differentiated such that they can benefit from communicating with each other. This reflects the idea that teams can benefit from the complementary skills of their members (Hamilton et al., 2003, Lazear and Shaw, 2007). The degree of specialization in the knowledge profiles hinges on transfer frictions. When transfer frictions are fixed, it is optimal to hire workers that are fully specialized in one dimension each, because under fixed transfer frictions workers can still transfer knowledge even if they know nothing about the dimension of their co-worker. When transfer frictions depend on the degree of differentiation between the knowledge profiles, workers' knowledge should in general comprise both knowledge dimensions. Optimal knowledge profiles depend on problem uncertainty and knowledge spillovers.

In terms of the organizational design, we find that it is always optimal to have an organization that engages in pure individual work or in pure teamwork. We find that there is a threshold in knowledge spillovers such that pure teamwork is optimal if spillovers are above this threshold. Sufficiently high knowledge spillovers make teamwork worthwhile, because both workers can learn from each other. Within pure teamwork, the problem-solving process is either managed by the organizational designer in that they choose workers' time allocations or the team itself manages the allocation of their time. The latter we refer to as self-managed team. Self-managed teams arise as corner solutions when knowledge spillovers are perfect or when different problem types are equally likely to be drawn, i.e., problem uncertainty is very high. This speaks to the fact that, as empirical studies showed, self-managed teams perform better than management-led teams when tasks are unpredictable (Rousseau and Aubé, 2010). Furthermore, we find that the designer's decision between pure individual work and pure teamwork also depends on the interaction between knowledge spillovers and the uncertainty of problem types. For this part of the analysis we focus on fixed transfer frictions such that optimal knowledge profiles under teamwork do not depend on the degree of uncertainty. As before, we find that for sufficiently small spillovers, individual production dominates teamwork. However, for intermediate spillovers, pure teamwork is optimal when uncertainty of problem types is intermediate. For sufficiently high spillovers, pure teamwork is optimal when uncertainty of problem types is below a threshold. In teamwork, high problem uncertainty can be compensated with high knowledge spillovers.

In an extension, we add a third problem that can arise supplementary to the problems in our baseline model. We want to study whether higher uncertainty changes the organizational structure. The additional problem requires workers to be equally knowledgeable in both dimension. This problem does not impact the designer's decision on the organizational structure. Therefore, the results are not qualitatively different to that effect. In Appendix 2.B, we include a second extension. We add a third knowledge dimension to increase the complexity of solving a problem. The organization hires three workers that each need to solve one problem from a set of three problem types. In this extension, we assume that transfer frictions are fixed. In terms of optimal organizational design, we find that for sufficiently high spillovers pure teamwork is optimal. Again, self-managed teams arise endogenously as corner solutions. Interestingly, when it is not unambiguous which of the three problem types is least likely to be drawn, there exists a partially self-managed team. The organizational designer directs parts of the communication between workers and leaves some parts to be determined by the workers themselves.

We want to point to two results in our model that we want to extend in future research. First, self-managed teams as optimal organizational design only arises as a corner solution in our model when spillovers are perfect or when different problem types arise with the same probability. We want to find a way to obtain self-managed teams as an interior solution without including a technological advantage for teamwork.

Closely connected to this result is the second point that we want to focus on in future research. In our model, we find that either pure teamwork or pure individual work is optimal because production is linear in the unit of time workers are allotted. However, in reality organizations often combine individual work with teamwork, e.g. by first working individually and when a solution is not reached quickly enough workers switch to teamwork. Such an organizational design cannot be obtained in our model. In future research, it would be interesting to extend our model by a production function that depends on time in a non-linear way. Is the optimal organization then a hybrid of teamwork and individual production? What are the optimal knowledge profiles for workers?

Another interesting extension includes the option for the designer to invest in learning about the problem uncertainty. Before the organizational designer hires workers and chooses an organizational design, they can decide whether to pay a fixed cost to learn about the problem uncertainty. This opens up the possibility to reduce uncertainty thereby increasing workers' specialization. If the cost of screening problem types is too high, the organizational designer can still implement self-managing teams as is optimal in our baseline for high problem uncertainty.

Last but not least, a logical extension of our model also needs to address the incentive system of such an organization. How can the organization induce knowledge transfer in teamwork? What kind of incentives does an organization choose if production is a hybrid of individual work and teamwork?

2.A Appendix: Proofs

Proof of Lemma 2.1

The organizational designer maximizes the total expected output of the organization or, equivalently under individual work, a single worker's expected output,

$$\max_{i\in[0,1]} ri + (1-r)\sqrt{1-i^2},$$

for $i = a, b$. For $r = 1$, the objective function is monotonically increasing in i so that we obtain a corner solution where the optimal i equals 1. For $r \in [1/2, 1)$, the optimal solution is characterized by the first-order condition,

$$r - (1-r)\frac{i}{\sqrt{1-i^2}} = 0,$$

because the objective function is strictly concave,

$$\frac{\partial^2 Q_j}{\partial i^2} = -(1-r)\left[\frac{\sqrt{1-i^2}}{1-i^2} + \frac{i^2}{(1-i^2)^{3/2}}\right] < 0,$$

for $j = A$, $i = a$ and $j = B$, $i = b$. We thus obtain the optimal, identical knowledge profiles, $a^I = b^I$, presented in Lemma 2.1.

Proof of Lemma 2.2

The organizational designer solves

$$\max_{a,b\in[0,1]} Q^T(a,b)$$

$$= \max_{a,b\in[0,1]}(1+s)(ra+(1-r)\sqrt{1-b^2}) - [(1-r)(t_A^l + st_A^h) + r(t_A^h + st_A^l)]K(a,b).$$

For $r = 1$, the objective function boils down to $(1+s)a - (t_A^h + st_A^l)K(a,b)$, which implies that identical knowledge for both workers as well as maximum knowledge in dimension 1 for worker A is optimal. Thus, $a^T = b^T = 1$.

Now consider $r \in [1/2, 1)$. The expected output is strictly concave since $K(a,b)$ is strictly convex while the Hessian matrix of $\bar{Q}^T(a,b) = ra + (1-r)\sqrt{1-b^2}$ reveals that $\bar{Q}^T$ is weakly concave

$$\text{Hess}(\bar{Q}^T(a,b)) = \begin{bmatrix} 0 & 0 \\ 0 & \frac{-(1-r)(\sqrt{1-b^2}+b^2)}{\sqrt[3]{1-b^2}} \end{bmatrix}.$$

The first derivatives of the objective function with respect to a and b are

$$(1+s)r - \left[(1-r)(t_A^l + st_A^h) + r(t_A^h + st_A^l)\right] K_a(a,b),$$

$$-(1+s)(1-r)\frac{b^T}{\sqrt{1-b^{T^2}}} - \left[(1-r)(t_A^l + st_A^h) + r(t_A^h + st_A^l)\right] K_b(a,b),$$

respectively. From $K_a(a,a) = K_b(a,a) = 0$, it follows that when workers have identical knowledge in dimension 1, the expected output is increasing in a and decreasing in b. Thus, starting from identical knowledge, it always pays off to marginally increase a or marginally decrease b, thereby utilizing benefits from specialization. Hence, we must have $a^T > b^T$.

Proof of Proposition 2.1

Recall that the organization's expected output is given by

$$t^w(Q_A + Q_B) + (1-t^w)(1+s)\bar{Q}^T - \left[(1-r)(t_A^l + st_A^h) + r(t_A^h + st_A^l)\right] K(a,b). \quad (2.6)$$

We first characterize the optimal choice of t_A^h and t_A^l. If $r = 1/2$, the expected output can be simplified to

$$\begin{aligned} & t^w(Q_A + Q_B) + (1-t^w)(1+s)\bar{Q}^T - \frac{1}{2}\left[(1+s)(t_A^l + t_A^h)\right] K(a,b) \\ &= t^w(Q_A + Q_B) + (1-t^w)(1+s)\left(\bar{Q}^T - \frac{1}{2}K(a,b)\right). \end{aligned} \quad (2.7)$$

Hence, the exact choice of t_A^l and t_A^h is immaterial. For the special case where $s = 1$, (2.6) simplifies to

$$\begin{aligned} & t^w(Q_A + Q_B) + 2(1-t^w)\bar{Q}^T - (t_A^l + t_A^h)K(a,b) \\ &= t^w(Q_A + Q_B) + (1-t^w)\left[2\bar{Q}^T - K(a,b)\right], \end{aligned}$$

which is independent of t_A^h and t_A^l. Thus, any choice of t_A^h and t_A^l that satisfies $t_A^h + t_A^l = 1 - t^w$ is optimal.

Now suppose that $r \in (1/2, 1)$. Then, for any fixed t^w, the variables t_A^l and t_A^h should be chosen such that the term in square brackets in (2.6) is minimized. As $r > 1/2$ and $s < 1$, the organizational designer should set $t_A^h = 0$ and $t_A^l = 1 - t^w$. We can then use $t_A^h = 0$ and $t_A^l = 1 - t^w$ to rewrite the expected output such that

$$
\begin{aligned}
&t^w(Q_A + Q_B) + (1+s)(1-t^w)\bar{Q}^T - [(1-r)(1-t^w) + rs(1-t^w)]\, K(a,b) \\
&\quad = t^w(Q_A + Q_B) + (1-t^w)\left[(1+s)\bar{Q}^T - (1 - r(1-s))K(a,b)\right]. \qquad (2.8)
\end{aligned}
$$

Note that, for $r = 1/2$, the expression in (2.8) is identical to the expression in (2.7). Thus, for any $r \in [1/2, 1)$, the organizational designer's objective function can be simplified to (2.8).

We next characterize the optimal t^w. Because the expected output, as given in (2.8), is linear in t^w, it is maximized by setting either $t^w = 0$ or $t^w = 1$. Setting $t^w = 0$ is strictly optimal if and only if

$$
\max_{a,b\in[0,1],a\geq b} Q_A + Q_B < \max_{a,b\in[0,1],a\geq b} (1+s)\bar{Q}^T - (1 - r(1-s))K(a,b). \qquad (2.9)
$$

If $s = 0$, inequality (2.9) does not hold as $Q_A + Q_B > \bar{Q}^T$ for all a, b. Thus, $t^w = 1$ is optimal. If $s = 1$, inequality (2.9) becomes

$$
\max_{a,b\in[0,1],a\geq b} Q_A + Q_B < \max_{a,b\in[0,1],a\geq b} 2\bar{Q}^T - K(a,b). \qquad (2.10)
$$

From Lemma 2.1, choosing $a = b = a^I$ solves the problem $\max_{a,b\in[0,1],a\geq b} Q_A + Q_B$. Moreover, for $a = b = a^I$ both sides of inequality (2.10) are identical. From Lemma 2.2, however, we know that $\max_{a,b\in[0,1],a\geq b} 2\bar{Q}^T - K(a,b)$ is solved by heterogeneous knowledge profiles $a^T > b^T$. Hence, inequality (2.10) is always satisfied, which implies that $t^w = 0$ is optimal in case $s = 1$. Finally, by the envelope theorem, the first derivative of the right-hand side of (2.9) with respect to s is

$$
\bar{Q}^T(a^T, b^T) - rK(a^T, b^T) = r(a^T - K(a^T, b^T)) + (1-r)\sqrt{1 - (b^T)^2} = Q_B^T(a^T, b^T),
$$

which is non-negative. The right-hand side of (2.9) is thus increasing in s, which implies that there must be a threshold $\bar{s}(r) \in (0, 1)$ as described in the proposition.

Proof of Proposition 2.2

First, we can observe that pure individual work always dominates pure teamwork if $r = 1$. This is because $Q^T(1) = 1 + s(1 - \bar{K}) < 2 = Q^I(1)$ for all $s \in [0, 1]$. Note that $Q^T(r)$ is linear and increasing in r. Moreover, it can be shown that $Q^I(r)$ is strictly convex and increasing in r and that $Q_r^I(1/2) = 0$. It follows that, if $Q^I(1/2) < Q^T(1/2)$, then there must be a threshold $\bar{r} \in (\frac{1}{2}, 1)$ as described in case (iii) of the proposition. The inequality $Q^I(1/2) < Q^T(1/2)$ is equivalent to $s > \frac{\sqrt{2}}{1-\bar{K}/2} - 1$.

If $s = \frac{\sqrt{2}}{1-\bar{K}/2} - 1$, then $Q^I(1/2) = Q^T(1/2)$. Because $Q_r^I(1/2) = 0$ while $Q_r^T(1/2) > 0$, pure individual work is weakly optimal for $r = 0$ and strictly optimal if r is sufficiently high.

Now suppose that s decreases, starting from $s = \frac{\sqrt{2}}{1-\bar{K}/2} - 1$. Then, $Q^T(r)$ and $Q^I(r)$ at first have exactly two intersections such that $Q^T(r) > Q^I(r)$ for intermediate r, which corresponds to case (ii) of the proposition. As s continues to decrease, at some point, $Q^T(r) < Q^I(r)$ for all $r \in [1/2, 1]$. This is true because, at $s = 0$, we have $Q^T(r) = 1 - (1-r)\bar{K} < 1$ for all r, whereas $Q^I(r) \geq \sqrt{2}$.

Proof of Corollary 2.1

Recall the overall expected output for this extension

$$Q_P(a,b) = t^w(Q_{P,A} + Q_{P,B}) + (1-t^w)(1+s)\bar{Q}_P^T$$
$$- \left[r(t_A^h + st_A^l) + q(t_A^l + st_A^h) + \frac{1}{\sqrt{2}}(1-r-q)(1+s)(1-t^w) \right] K(a,b). \quad (2.11)$$

To characterize the optimal choice of t_A^h and t_A^l, we first look at the special case of $r = q = \frac{1}{3}$ such that all problem types are equally likely. The overall expected output can be simplified to

$$t^w(Q_{P,A} + Q_{P,B}) + (1-t^w)(1+s)\bar{Q}_P^T$$
$$- \left[\frac{1}{3}(1+s)(t_A^h + t_A^l) + \frac{1}{3\sqrt{2}}(1-r-q)(1+s)(1-t^w) \right] K(a,b). \quad (2.12)$$

Hence, when $r = q = \frac{1}{3}$ the exact choice of t_A^l and t_A^h is immaterial. For the special case where $s = 1$ the overall expected output simplifies to

$$t^w(Q_{P,A} + Q_{P,B}) + 2(1-t^w)\bar{Q}_P^T - (1-t^w)\left[r + q + \frac{2}{\sqrt{2}}(1-r-q) \right] K(a,b).$$

Again, any choice that satisfies $t_A^h + t_A^l = 1 - t^w$ is optimal. Now we focus on the cases where $r, q \in (0,1)$. For any fixed t^w, the variables t_A^h and t_A^l should be chosen such that the term in square brackets in (2.4) is minimized. Notice that the additional third problem has no influence on the designer's choice of t_A^h and t_A^l. Therefore, when $r > q$ and $s < 1$, $t_A^l = 1 - t^w$ while $t_A^h = 0$ and vice versa for $r < q$.

Now we can characterize the optimal choice of t^w. For $r > q$ we can re-write the expected output as

$$t^w(Q_{P,A} + Q_{P,B}) + (1 - t^w)(1 + s)\bar{Q}_P^T$$
$$- (1 - t^w)(rs + q + \frac{1}{\sqrt{2}}(1 - r - q)(1 + s))K(a, b).$$

For $r < q$ it can be simplified to

$$t^w(Q_{P,A} + Q_{P,B}) + (1 - t^w)(1 + s)\bar{Q}_P^T$$
$$- (1 - t^w)(r + qs + \frac{1}{\sqrt{2}}(1 - r - q)(1 + s))K(a, b).$$

In both cases the expected output is linear in t^w. Hence, it is maximized by $t^w \in \{0, 1\}$. Setting $t^w = 0$ is optimal if and only if

(i) in case $r > q$:

$$\max_{a,b \in [0,1],\ a \geq b} Q_{P,A} + Q_{P,B} < \max_{a,b \in [0,1],\ a \geq b} (1 + s)\bar{Q}_P^T - (rs + q + \frac{1}{\sqrt{2}}(1 - r - q)(1 + s))K(a, b) \quad (2.13)$$

(ii) in case $q > r$:

$$\max_{a,b \in [0,1],\ a \geq b} Q_{P,A} + Q_{P,B} < \max_{a,b \in [0,1],\ a \geq b} (1 + s)\bar{Q}_P^T - (r + qs + \frac{1}{\sqrt{2}}(1 - r - q)(1 + s))K(a, b) \quad (2.14)$$

For both (2.13) and (2.14), the inequality isn't satisified for $s = 0$ for any a, b. Therefore, $t^w = 1$ is optimal. For $s = 1$, LHS of both (2.13) and (2.14) is maximized for some identical knowledge profile $a = b$, while RHS are equivalent to LHS for $a = b$. However, RHS are maximized for some $a_P^T \neq b_P^T$, thus $t^w = 0$ is optimal.

By the envelope theorem, the first derivative of RHS of (2.13) and (2.14) with respect to s are non-negative:

$$\bar{Q}_P^T - (r + \frac{1}{\sqrt{2}}(1 - r - q))K(a_P^T, b_P^T) = Q_{P,B}^T$$
$$\bar{Q}_P^T - (q + \frac{1}{\sqrt{2}}(1 - r - q))K(a_P^T, b_P^T) = Q_{P,A}^T,$$

respectively. For both cases (i) and (ii), the RHS is increasing in s which implies that there must be a threshold $\bar{s}_P(r) \in (0, 1)$ and $\bar{s}_P(q) \in (0, 1)$.

2.B Extensions: Organization with Three-dimensional Problems

In this extension, we study what happens when problems require three dimensional knowledge profiles. We assume that there are three problem types each located in the three-dimensional space. In order to stay with our one-to-one relation of workers to problem types from the baseline model, we assume that there are three workers. We want to study whether this set-up changes the organizational structure.

Model

In this set-up, we have three workers $j = A, B, C$ who each draw a problem and have one unit of time to solve it. In order to solve a problem, workers now need a three-dimensional knowledge profile $\boldsymbol{i} = (i_1, i_2, i_3)$ for $\boldsymbol{i} = \boldsymbol{a}, \boldsymbol{b}, \boldsymbol{c}$. Knowledge is non-negative, $i_1, i_2, i_3 \geq 0$. We assume that a worker's knowledge profile corresponds to a specific point on the sphere with radius 1 in the three-dimensional space reflecting the knowledge profiles, i.e., $i_1^2 + i_2^2 + i_3^2 = 1$. This means, we expand the model from a circle with radius 1 to a sphere with radius 1. Hence, we can express everything in terms of dimensions 1 and 2, since $i_3 = \sqrt{1 - i_1^2 - i_2^2}$. Note that before we were able to express everything in dimension 1 only. We assume that each worker is more knowledgeable in one dimension than their colleagues, i.e, $a_1 \geq b_1, c_1$, $b_2 \geq a_2, c_2$ and $\sqrt{1 - c_1^2 - c_2^2} \geq \sqrt{1 - a_1^2 - a_2^2}, \sqrt{1 - b_1^2 - b_2^2}$.[59] Notice that this is not a complete ordering of knowledge profiles. Among workers who are not more knowledgeable than their colleague in a specific dimension, it is not obvious who is more knowledgeable than the other.

Problems are characterized by the knowledge that is needed to solve them with certainty, $\boldsymbol{p} = (p_1, p_2, p_3)$ with $p_1, p_2, p_3 \geq 0$ and $p_1^2 + p_2^2 + p_3^2 = 1$ such that $p_3 = \sqrt{1 - p_1^2 - p_2^2}$. We focus on three specific problem types: $\boldsymbol{p} = (1, 0, 0)$, $\boldsymbol{p} = (0, 1, 0)$ and $\boldsymbol{p} = (0, 0, 1)$. Dimension 1 and 2 of a problem is the realization of a random variable such that $Pr[(p_1, p_2) = (1, 0)] = \alpha$, $Pr[(p_1, p_2) = (0, 1)] = \beta$ and $Pr[(p_, p_2) = (0, 0)] = 1 - \alpha - \beta$, where $\alpha, \beta \in (0, 1)$ and $\alpha + \beta \leq 1$. Problem types are unknown ex ante, so workers do not know which knowledge dimension is relevant to solve the problem. Compared to the baseline model, one can argue that three-dimensional problems introduce a higher level of difficulty in the sense that workers need to be specialized in one out of three dimensions.

As before, solving a problem occurs with probability $i_1 p_1 + i_2 p_2 + i_3 p_3$. The probability can only be equal to 1 if there is an exact match between knowledge profile and problem type. The larger the angle between problem vector and knowledge profile, the less likely the worker is to solve a given problem.

[59] This assumption is not without loss of generality, as we cannot exclude that it might be optimal to have one agent who is more knowledgeable in two dimensions.

The organizational designer determines the optimal production process by choosing how workers spend their time. Particularly, the designer decides how much time a worker spends working individually, t_j^w, how much time they spend helping, t_j^h, and how much time they spend learning, t_j^l. Overall, they have one time unit to solve a problem, i.e., $t^w + t_j^h + t_j^l = 1$ for all $j = A,\ B,\ C$.

When workers engage in pure individual production, we do not diverge from the assumptions of the baseline model. When $t_j^w = 1$ for all $j = A, B, C$, the expected output of a worker is

$$Q_D^j(i_1, i_2) := \alpha i_1 + \beta i_2 + (1-\alpha-\beta)\sqrt{1 - i_1^2 - i_2^2},$$

for all $j = A, B, C$ and $i = a, b, c$. The expected output takes into account that there are three problem types that each require specialization in a different knowledge dimension in order to be solved.

For teamwork, we need to establish some rules to guide the communication process with three workers. We assume for now that workers can discuss one problem at a time and that all workers are involved in the discussion.[60] Since all three workers are involved in the same communication process, they all spend the same amount of time working individually, i.e., $t_A^w = t_B^w = t_C^w := t^w$. The time a worker spends helping their colleagues is t_j^h for all $j = A,\ B,\ C$. Since two workers simultaneously help their third colleague, it must hold that $t_A^h + t_B^h + t_C^h \leq 2$. The time a worker spends learning is t_j^l. Since one worker listens to both colleagues simultaneously, it must hold that $t_A^l + t_B^l + t_C^l \leq 1$.Under pure teamwork, $t^w = 0$, a worker who receives help from their colleagues all the time ($t_j^l = 1$), has an expected output of

$$Q_{D,A}^T = \alpha a_1 + \beta(b_2 - \bar{K}) + (1-\alpha-\beta)(\sqrt{1 - c_1^2 - c_2^2} - \bar{K})$$

$$Q_{D,B}^T = \alpha(a_1 - \bar{K}) + \beta b_2 + (1-\alpha-\beta)(\sqrt{1 - c_1^2 - c_2^2} - \bar{K})$$

$$Q_{D,C}^T = \alpha(a_1 - \bar{K}) + \beta(b_2 - \bar{K}) + (1-\alpha-\beta)\sqrt{1 - c_1^2 - c_2^2}$$

The expected outputs reflect that each worker has one dimension where they are more knowledgeable than their colleagues and two dimensions where they can learn from their colleagues. In the dimensions where they learn from their colleagues, workers face a fixed knowledge friction, $\bar{K} \in (0, 1)$, that is similar to the transfer frictions in Section 2.3.4. Transfer frictions, therefore, do not depend on workers' knowledge profiles, such that knowledge can even be transferred if workers know nothing about the dimension they are learning about. The total expected output of the organization is then given by

[60] To be transparent, this means that a worker can learn from both colleagues at the same time.

$$
\begin{aligned}
Q_D :=& t^w(Q_D^A + Q_D^B + Q_D^C) + (st_A^h + t_A^l)Q_{D,A}^T + (st_B^h + t_B^l)Q_{D,B}^T \\
&+ (st_C^h + t_C^l)Q_{D,C}^T. \qquad (2.15)
\end{aligned}
$$

The first term of (2.15) reflects the expected output from individual work, while the other terms originate from expected output in teamwork. Notice that we also take into account that when workers spend their time helping their colleagues they can also learn from both colleagues via knowledge spillovers, $s \in [0, 1]$.

Individual Production

First, we look at knowledge profiles under pure individual work, $t^w = 1$. The expected output of a worker $j = A, B, C$ is

$$
Q_j(i_1, i_2) = \alpha i_1 + \beta i_2 + (1 - \alpha - \beta)\sqrt{1 - i_1^2 - i_2^2}
$$

for all $i = a, b, c$. Under pure individual work the organizational designer maximizes the total expected output under $t^w = 1$ with respect to the knowledge dimension i_1, i_2.

Lemma 2.B.1 *Under pure individual production, $t^w = 1$, the organizational designer hires workers A, B and C with identical knowledge profiles such that*

$$
i_1^I = \frac{\alpha}{\sqrt{(1 - \alpha - \beta)^2 + \alpha^2 + \beta^2}},
$$

$$
i_2^I = \frac{\beta}{\sqrt{(1 - \alpha - \beta)^2 + \alpha^2 + \beta^2}},
$$

for all $i = a,\ b,\ c$.

Proof.

The designer's objective function is

$$
\max_{i_1, i_2} \alpha i_1 + \beta i_2 + (1 - \alpha - \beta)\sqrt{1 - i_1^2 - i_2^2}
$$

for $i = a, bc$. Solving the first-order conditions for knowledge in dimension 1 and 2 yields

$$
\frac{\alpha}{(1 - \alpha - \beta)i_1} = \frac{1}{\sqrt{1 - i_1^2 - i_2^2}},
$$

$$
\frac{\beta}{(1 - \alpha - \beta)i_2} = \frac{1}{\sqrt{1 - i_1^2 - i_2^2}},
$$

which gives the optimal knowledge profiles because the objective function is concave. In case one of the problem types is drawn with certainty, i.e., $\alpha = 1$ or $\beta = 1$ or $1 - \alpha - \beta = 1$, the expected output is monotonically increasing in the respective knowledge dimension. Therefore, in this special cases we reach a corner solution for a worker fully specialized in the respective dimension. For example, if $\alpha = 1$, expected output is monotonically increasing in i_1, and thus all workers are optimally fully specialized in dimension 1. ■

As in the baseline model, we observe that it is optimal to choose workers with identical knowledge profiles. Knowledge dimension 1 is increasing in α and decreasing in β while it is vice versa for dimension 2. This means if a problem that is intensive in dimension 1 is more likely, then optimally knowledge in dimension 1 increases and it decreases when a problem that is intensive in dimension 2 is more likely. When each problem type is drawn with the same probability ($\alpha = \beta = \frac{1}{3}$), workers have the same degree of specialization in each dimension:

$$i_1^I = i_2^I = i_3^I = \frac{1}{\sqrt{3}}.$$

On the other hand, if one problem type arises with certainty, e.g., $\alpha = 1$ so that problem type $\boldsymbol{p} = (1, 0, 0)$ is drawn, all workers are optimally fully specialized in dimension 1. Notice that these are the only situations where workers are fully specialized in pure individual production. The results are qualitatively equivalent to the baseline model.

Team Production

When we look at pure teamwork ($t^w = 0$), a worker who receives help from their colleagues all the time ($t_j^l = 1$), has an expected productivity of

$$Q_{D,A}^T = \alpha a_1 + \beta(b_2 - \bar{K}) + (1 - \alpha - \beta)(\sqrt{1 - c_1^2 - c_2^2} - \bar{K}),$$

$$Q_{D,B}^T = \alpha(a_1 - \bar{K}) + \beta b_2 + (1 - \alpha - \beta)(\sqrt{1 - c_1^2 - c_2^2} - \bar{K}),$$

$$Q_{D,C}^T = \alpha(a_1 - \bar{K}) + \beta(b_2 - \bar{K}) + (1 - \alpha - \beta)\sqrt{1 - c_1^2 - c_2^2}.$$

Workers can learn from their colleagues in the dimensions they are not the most knowledgeable, however, they incur the fixed transfer frictions that diminish the transfer. Using the constraints on time allocation, the total expected output from pure teamwork is given by

$$\begin{aligned} Q_D^T =& (1 + 2s)\bar{Q}_D^T - (t_A^l + st_A^h)(1 - \alpha)\bar{K} \\ & - (t_B^l + st_B^h)(1 - \beta)\bar{K} - (t_C^l + st_C^h)(\alpha + \beta)\bar{K}, \end{aligned} \tag{2.16}$$

where $\bar{Q}_D^T := \alpha a_1 + \beta b_2 + \gamma\sqrt{1-c_1^2-c_2^2}$ denotes the expected output from teamwork if there were no transfer frictions. When transfer frictions are fixed, the organizational designer decides to hire workers who are fully specialized, because transferring knowledge is possible even if a co-worker has no knowledge in the required dimension. Hence, the designer optimally hires workers with $\boldsymbol{a}^T = (1,0,0)$, $\boldsymbol{b}^T = (0,1,0)$ and $\boldsymbol{c}^T = (0,0,1)$. Each worker is specialized in one dimension. The optimal expected output from pure teamwork ($t^w = 0$) is then

$$Q_D^T(\boldsymbol{a}^T, \boldsymbol{b}^T, \boldsymbol{c}^T) = (1+2s) - (t_A^l + st_A^h)(1-\alpha)\bar{K} - (t_B^l + st_B^h)(1-\beta)\bar{K} - (t_C^l + st_C^h)(\alpha+\beta)\bar{K}.$$

Organizational Design

When we turn to the question of the optimal organizational design, the organizational designer wants to maximize the total expected output with respect to t_j^h, t_j^l and t^w for all $j = A,\ B,\ C$. The total expected output from (2.15) can be re-written as

$$Q_D = t^w(Q_D^A + Q_D^B + Q_D^C) + (1-t^w)(1+2s)\bar{Q}_D^T - ((t_A^l + st_A^h)(1-\alpha) + (t_B^l + st_B^h)(1-\beta) + (t_C^l + st_C^h)(\alpha+\beta))\bar{K}. \tag{2.17}$$

Notice that the term $(1-t^w)(1+2s)$ reflects the notion that a worker can learn from both colleagues and both colleagues can simultaneously help them. The special case where a problem is certain ex ante, it is optimal to hire three workers who are specialized in the relevant knowledge dimension so they can solve their problems under pure individual work. Teamwork and communication is detrimental when problem types are certain ex ante because a worker who helps their colleague cannot work on their own problem.

Therefore, we focus on situations where problem types are not certain ex ante, i.e. $\alpha, \beta \in (0,1)$. Following Proposition 2.1, we can characterize the optimal organizational design depending on knowledge spillovers, s.

Lemma 2.B.2 *Suppose problem types are uncertain, $\alpha, \beta \in (0,1)$. Pure teamwork ($t^w = 0$) is optimal if s is sufficiently high. Otherwise, pure individual work is optimal. Problem solving in teams is structured as follows:*

(i) If $\alpha = \beta = \frac{1}{3}$, any allocation of t_j^h and t_j^l for $j = A,\ B,\ C$ is optimal that satisfies $t_A^l + t_B^l + t_C^l = 1$ and $t_A^h + t_B^h + t_C^h = 2$.

(ii) If $\frac{1-\beta}{2} < \alpha < \beta$, workers B and C help worker A with their problem all the time, i.e., $t_A^l = 1$, $t_B^h = t_C^h = 1$. Analogous for any case where one of $1-\alpha$, $1-\beta$ and $\alpha+\beta$ is strictly smaller than the other two terms.

(iii) If $\alpha = \beta > \frac{1}{3}$, worker C spends all their time helping ($t_C^h = 1,\ t_C^l = 0$) while any pair $t_A^l + t_B^l = 1$ and $t_A^h + t_B^h = 1$ is optimal. Analogous for any case where two of the terms $1-\alpha$, $1-\beta$ and $\alpha+\beta$ are equivalent and smaller than the third term.

(iv) If $s = 1$ and $\bar{K}$ sufficiently small, any allocation of t_j^h and t_j^l for $j = A,\ B,\ C$ is optimal that satisfies $t_A^l + t_B^l + t_C^l = 1$ and $t_A^h + t_B^h + t_C^h = 2$.

Proof.

Recall that the total expected output is given by

$$Q_D = t^w(Q_D^A + Q_D^B + Q_D^C) + (1-t^w)(1+2s)\bar{Q}_D^T$$
$$- \Big((t_A^l + st_A^h)(1-\alpha) + (t_B^l + st_B^h)(1-\beta) + (t_C^l + st_C^h)(\alpha+\beta)\Big)\bar{K}. \qquad (2.18)$$

We first characterize the optimal choice of $t_j^l,\ t_j^l$ for $j = A,\ B,\ C$.

(i) For $\alpha = \beta = \frac{1}{3}$ the total expected output simplifies to

$$t^w(Q_D^A + Q_D^B + Q_D^C) + (1-t^w)(1+2s)(\bar{Q}_D^T - \frac{2}{3}\bar{K})$$

such that the exact choice of $t_j^h,\ t_j^h$ for $j = A,\ B,\ C$ is immaterial. In this case pure teamwork is optimal if

$$s > \frac{3\sqrt{\alpha^2+\beta^2+(1-\alpha-\beta)^2}}{2(1-2/3\bar{K}} - \frac{1}{2}.$$

(ii) If $1-\alpha$, $1-\beta$ or $\alpha+\beta$ is strictly smaller than the other two terms, the organizational designer wants to minimize the impact of the transfer frictions by maximizing the time spent learning, $t_j^l = 1-t^w$, of the worker associated with the strictly smallest term of $1-\alpha$, $1-\beta$ and $\alpha+\beta$. This implies that the other two workers each spend $t_{-j}^h = 1-t^w$ helping their colleague; for $j = A, B, C$. Pure teamwork is optimal in this specific case if

$$s > \frac{3\sqrt{\alpha^2+\beta^2+(1-\alpha-\beta)^2} + (1-\alpha)\bar{K} - 1}{2-(1+\alpha)\bar{K}}.$$

(iii) If two of the three terms $1-\alpha$, $1-\beta$ or $\alpha+\beta$ are equivalent and smaller than the third, the organizational designer minimizes the impact of $\bar{K}$ on the total expected output by choosing $t_j^h = 1-t^w$ for the worker associated with the largest of the three terms $1-\alpha$, $1-\beta$ or $\alpha+\beta$. While the exact choice of time allocations for the other two workers is immaterial as long as they satisfy the time constraints. Pure teamwork is optimal if

$$s > \frac{3\sqrt{\alpha^2+\beta^2+(1-\alpha-\beta)^2} + (1-\alpha)\bar{K} - 1}{2-(1+\alpha)\bar{K}}.$$

(iv) If $s = 1$ the total expected output simplifies to

$$Q_D = t^w(Q_D^A + Q_D^B + Q_D^C) + (1 - t^w)[3\bar{Q}_D^T - 2\bar{K}],$$

such that the exact choice of $t_j^h,\ t_j^h$ for $j = A,\ B,\ C$ is immaterial. Pure teamwork is optimal if

$$\bar{K} < \frac{3}{2}(1 - \sqrt{\alpha^2 + \beta^2 + (1 - \alpha - \beta)^2}.$$

Next, we characterize the optimal choice of t^w. In (i)-(iv), the total expected output is linear in t^w, such that it is maximized by choosing $t^w = 0$ or $t^w = 1$. For sufficiently high s it is then optimal to choose pure teamwork. ■

Lemma 2.B.2 is similar to Proposition 2.1. Even though we do not find a specific threshold, we can define a certain level of knowledge spillovers above which pure teamwork is optimal. When spillovers are sufficiently high, communication between workers is worthwhile not only for the worker who gets help but also for the workers who are helping.

Particularly, the second part of Lemma 2.B.2 resembles Proposition 2.1 in that it is also concerned with the optimal time allocations under pure teamwork. Special cases (i) and (iv) reveal a situation where the specific choice of t_j^h and t_j^l is immaterial. We refer to teamwork in these cases as self-managed teamwork, because the team decides how to allocate their time. Hence, they structure the problem solving process on their own.

In case (ii), it is unambiguous which worker the organizational designer assigns to spend all their time learning to minimize transfer frictions because one of the terms in (2.17) associated with $t_j^l + st_j^h$ is smaller than the other two. This choice implies that the other two workers spend all their time helping. The team is managed by the organizational designer and cannot self-manage.

In case (iii), it is not clear which worker spends all their time learning. Two of the terms associated with $t_j^l + st_j^h$ in (2.17) are equivalent and smaller than the third term. Hence, in order to minimize transfer frictions the organizational designer decides that the worker associated with the largest term spends all their time helping. For the other two workers, the organizational designer is indifferent about how they spend their time. It needs to be satisfied the total time learning sums up to one and the total time spend helping sums up to two for all three workers. In this case, the organizational designer manages one communication channel, while giving the team authority to manage the other two communication channels on their own.

Chapter 3

One-sided Knowledge Transfer in Teams: The Role of Commitment

3.1 Introduction[61]

Knowledge is an important input factor for production especially in today's information economy where firms compete through creating new and advanced products. A firm's competitive advantage is built on the knowledge[62] that is accumulated and created by its employees (Davenport et al., 1998b, Feldman and Sherman, 2001, Grant, 1996, Romer and Kurtzman, 2004). Each employee brings their own set of skills to a firm which combined with other employees' knowledge creates new expertise and increases their productivity (Nonaka et al., 2000).[63] To use an employee's knowledge to its full potential, it must be shared with co-workers so that it disseminates and becomes part of the organization (Fahey and Prusak, 1998, Davenport et al., 1998b). Managing this process is a big challenge for firms (Fahey and Prusak, 1998, Prusak, 2001). Feldman and Sherman (2001) estimated that an organization employing 1,000 knowledge workers loses 2.5 to 3.5 million US Dollars due to inefficient knowledge management. Knowledge management is an integral part of leveraging an organization's full set of resources.

A key lever of effective knowledge management is to motivate workers to share their expertise instead of hoarding it. Since knowledge is inherent to individuals, the easiest way to transfer it is through formal and informal interactions (Davenport et al., 1998b). Take for example a group of workers who is assigned to work on a project. In regular meetings, lunches and phone calls, workers have ample chance to talk about the project, exchange ideas, experiences and knowledge. The newly appropriated expertise may help them tackle their individual tasks not only in the specific project but across all their tasks in their work. However, since knowledge "belongs" to an individual, they may have an incentive to hoard it. Exclusive knowledge can be used as a bargaining chip in negotiations and viewed as an advantage over competitors. Sharing such knowledge means losing the advantage (Bartol and Srivastava, 2002, Davenport et al., 1998b). Therefore, employees might be reluctant to share their knowledge. Furthermore, knowledge is sticky, i.e., it is costly to transfer in terms of time and effort that go into explaining and understanding (Davenport et al., 1998b, Nonaka et al., 2000), which also deters employees from engaging in a knowledge transfer.

In this context, the main aim of a firm is to identify how it can motivate workers to share their knowledge. This is especially important since interactions that lead to a knowledge transfer between workers are hardly verifiable even though they

[61] I thank Maren Hahnen, Anja Schöttner, Harvey Upton as well as participants of the Microeconomic Colloquium in Berlin for their helpful comments.

[62] I use the term knowledge to describe information as well as tacit and explicit knowledge – similar to Bartol and Srivastava (2002). For a differentiated definition of knowledge consult Davenport et al. (1998b) or Nonaka et al. (2000)

[63] Lazear and Shaw (2007) argue that cooperation between workers enhances productivity by combining complementary skills, which is a part of knowledge.

may be observable by a manager.[64] In this chapter, I answer the question how a principal can induce two agents to engage in a one-sided knowledge transfer. I develop a dynamic model where two risk-neutral and wealth-constrained agents are hired to each perform an individual task in a project. Before they address their task, they decide whether they want to transfer knowledge which increases the receiver's task-related productivity while it is costly for both sender and receiver. The principal can neither observe agents' task nor transfer effort level, they just receive a joint performance signal of the project. I study the optimal contracts when a principal can commit to a contract at the beginning of the game and when they can only offer a contract after agents already chose their transfer effort level. For the latter environment, it is important that the principal observes whether a knowledge transfer occurred, however, that information is not verifiable. I analyze how the principal can induce a transfer and under which conditions it is optimal to do so for each contractual environment. To evaluate the difference of the environments, I determine whether there is a value in commitment.

Solving the model for Nash equilibria, I find that with and without commitment a knowledge transfer can be optimal under specific conditions. When the principal cannot commit to a contract at the beginning of the game, the principal pays the agents a rent for their task effort. Given the agents engage in a knowledge transfer, the principal can pay the knowledge receiver a lower rent to induce a task effort because their productivity increases. Thus, a knowledge transfer can be cost-saving for the principal. A knowledge transfer is an equilibrium when it is optimal to offer a contract where both agents receive a positive rent only after the principal observed a non-verifiable transfer. When the principal does not observe a knowledge transfer, they can credibly threaten the agents to not pay both of them a rent. Therefore, the agents face a lower expected pay-off when they do not transfer knowledge due to the joint performance signal.

However, when the principal can commit to a contract at the beginning of the game, they pay the agents a rent for their task and their transfer effort(s). They can induce a knowledge transfer in equilibrium when they at least implement a task effort from the knowledge receiver, such that a transfer is worthwhile in terms of realizing the productivity increase. Off-equilibrium, that is when the agents do not engage in a knowledge transfer, the probability for a success must be lower than on-equilibrium path. In both contractual environments, the joint performance signal drives the knowledge transfer, in that the principal uses the fact that the outcome depends on both agents' task effort choice to induce them to choose a high transfer effort given it is the other agent's best response. In this model, it is not clear that commitment is always better for the principal even though the first-best allocation can be achieved under commitment. With commitment power, the principal pays the agents a rent

[64] Knowledge transfers are hard to grasp in that they are complicated to measure except if they take the form of contributions to company wikis or exchange forums (Davenport et al., 1998a), e.g. Stack Exchange.

that compensates them for their task and their transfer effort. Without commitment power a higher expected profit can be reached, because they only pay agents a rent that compensates them for their task effort and still induces a knowledge transfer.

This chapter is structured as follows. After classifying the chapter into the existing literature, I introduce the model set-up. In Section 3.3, I analyze the model with a principal who has no commitment power. This is followed by the analysis of the model with commitment. Before I conclude, I explore in Section 3.5 whether it is better to have commitment power.

3.1.1 Related Literature

This chapter is related to a set of articles on knowledge and information transfer, team theory and knowledge-based theory of the firm.

The article closest to this chapter is Siemsen et al. (2007). They study different types of linkages between employees and how a principal induces the employees to cooperate. Just as in my model, knowledge-linked agents can engage in a productivity-increasing knowledge transfer. In contrast to this chapter, the knowledge transfer in Siemsen et al. (2007) is two-sided. In a static model with risk-averse agents, they find that individual and group incentives are necessary to induce cooperative behavior. The agents transfer knowledge, if the recipient uses it to increase their outcome such that the sender can benefit from it through the group component of the incentives. This chapter, in contrast, studies a dynamic model with risk-neutral and wealth-constrained agents. Through a joint performance signal, the principal can motivate a non-verifiable knowledge transfer by paying each agent a rent. This implies that a team incentive is sufficient to induce a one-sided knowledge transfer.

d'Aspremont et al. (1998) and Severinov (2001) study knowledge transfer in R&D projects with competitive firms. d'Aspremont et al. (1998) focus on the issue of motivating knowledge transfer and effort. While exerting effort is a standard moral hazard problem, knowledge transfer is viewed as an adverse selection problem considering the strategic aspects of information exchange. Hence, d'Aspremont et al. (1998) examine the interaction between moral hazard and adverse selection, whereas Severinov (2001) considers a dual moral hazard problem, taking into account the flow of information between firms and the need to regulate the transfer of information. Both models have in common that they look at the strategic aspects of knowledge transfer in a setting with competitive firms. My model distinguishes itself from these as it focuses on intra-firm knowledge transfer without discussing implications outside of the firm.

Another environment where knowledge is shared are apprenticeships which are studied in Garicano and Rayo (2017) and Fudenberg and Rayo (2019) who build on each other. While Garicano and Rayo (2017) focus on the speed at which knowledge is transferred in the dynamic relationship between expert and novice, Fudenberg and Rayo (2019) expand the model by also considering the novice's effort. In the latter model, a principal shares knowledge with an apprentice in return for effort. The principal specifies the optimal effort path, task allocation and knowledge transfer. The optimal contract, however, is inefficient for the principal as they train the apprentice inefficiently slowly to reduce the apprentice's outside option. Both articles conclude on this same result. In addition, Fudenberg and Rayo (2019) show that the apprentice works inefficiently hard for the training. My set-up differs from these articles, as in my model neither sender nor recipient of knowledge have authority such that knowledge cannot be traded for effort. Furthermore, in the articles by Fudenberg and Rayo (2019) and Garicano and Rayo (2017) knowledge affects not only the novice's productivity but also their outside option, while in my model the knowledge transfer only has an effect on the receiver's productivity.

In addition, this chapter also contributes to the literature on team theory which studies incentives that induce cooperation between agents. In its general set-up, the effort choice in my model resembles a static version of the dynamic game in Che and Yoo (2001). They study the effect of repeated interaction on incentives for teams and find that repeated interaction between agents leads to peer pressure with a feasible punishment strategy. That way implicit incentives for agents increase and the principal can reduce explicit incentives. I study a two-period game, where the second period is based on the one-shot game in Che and Yoo (2001). However, the first period in my model is detached from Che and Yoo (2001) and examines a specific form of cooperation between agents, a knowledge transfer. The research on team theory originates from Holmstrom (1982) who studies moral hazard in a multi-agent setting. He focuses on the role of free-riding and competition between agents in determining optimal incentives. His two main findings are: firstly, group incentives can resolve the free-riding problem and, secondly, competition in the form of relative performance evaluation reduces moral hazard costs due to information elicited through the contract.

In this tradition, Holmstrom and Milgrom (1990) investigate under which conditions a principal wants to compensate agents as a team. They find that even when two agents perform technologically independent tasks, team compensation can be optimal. It is optimal when agents are risk-averse and face negatively correlated risks. If risks are interdependent, each agent's output signal contains information about the other agent as well. According to the informativeness principle, this information should be used in compensation schemes to reduce the risk premium paid to the agents. Itoh (1991, 1992) researches in a similar vein, analyzing at what point a principal wants to induce cooperation among groups of agents. In Itoh (1991), agents can engage in an effort task and in helping another agent, where helping affects the task outcome. The principal induces teamwork, i.e., agents work on their task and also help each other if agents do not free-ride on the help they receive but increase their task-related effort with help. In his later article Itoh (1992) there are two agents who each exert effort in the same two tasks. This way, the agents can act as a team. He shows that if agents are compensated as a team, the principal benefits from side-contracting of agents. The principal can induce the same effort levels while paying a lower risk premium due to the agents monitoring activity.

Related to Holmstrom and Milgrom (1990) and Itoh (1991, 1992) is Macho-Stadler and Perez-Castrillo (1993) who discuss the optimal incentive structure for cooperative behavior when cooperation between risk-averse agents is technically profitable and agents have different levels of commitment capacity to cooperate. In a team setting, agents make all their decisions together and the efficient level of cooperation can be realized with a sharing rule. However, the principal gives up the power to determine individual rewards. A group of agents that only decide on their collaboration level together but not on their individual efforts, reaches a higher than optimal cooperation level. The articles on team theory all study general cooperative behavior and how a principal can induce it. In all these articles, cooperative behavior affects the task outcome. I contribute to this literature by focusing on knowledge transfer as a specific type of cooperation that affects the productivity of the agent who receives knowledge. The principal pays the agents rents to exert effort for individual tasks of a joint project and thus can also induce the agents to cooperate.

Lastly, Grant (1996), Nickerson and Zenger (2004) and Osterloh and Frey (2000) qualitatively develop a knowledge-based theory of the firm and discuss coordination problems that arise from using, generating and transferring knowledge. Garicano (2000) regards knowledge as the central ingredient to production in his model and identifies acquisition, communication and use of knowledge as the coordination problems that arise in organizations. Such problems emerge because knowledge is dispersed among workers who face a time constraint. In his model, an organization optimally takes the form of a knowledge-based hierarchy. That is, workers on the production floor try to solve problems and ask managers in the next higher layer for help if they cannot solve a problem. Agents in each hierarchy layer have the same knowledge which is ranked by complexity. This literature deals with coordination problems of knowledge and complements the literature on incentive problems that concern knowledge. Together they explain the role knowledge plays in a firm and how it can be managed. This chapter contributes to this literature by helping to understand how a knowledge transfer, that only benefits one agent, can be induced.

3.2 Model

A principal hires two agents, A and B, to each perform a task. All parties are risk-neutral and the agents are protected by limited liability such that the principal cannot pay negative wages.[65] I assume that the agents' outside option is zero. If the principal hires the agents, they interact with each other for two periods, $t = 1, 2$.

In $t = 1$, agent A can transfer knowledge to agent B such that B is more productive in the following period. Both agents must simultaneously decide whether

[65] A simple explanation for this assumption is that the agents have no wealth.

they want to transfer knowledge. They make a binary effort decision, $e_i \in \{0,1\}$ for $i = A, B$ at the cost of $\rho e_i \geq 0$ with $\rho > 0$. The transfer is costly for agent A because they have to "teach" agent B. For B it is costly because they have to "learn" from A. The knowledge transfer takes place if and only if both agents exert a high effort, i.e., $e_A = e_B = 1$ and thus $T = 1$. Otherwise, knowledge is not transferred, i.e., $T = 0$. The principal cannot observe the agents effort choice but they can observe whether a transfer took place. The information, however, is not verifiable. This can happen for example when a principal witnesses two agents talking about work. The interaction between the agents suggests that some form of knowledge transfer might take place, however, it is not verifiable by a third party. Such situations are common in various organizations where one worker needs help with a task they have less experience in. They ask a co-worker for help who, e.g., was assigned a similar task before and can, therefore, talk from experience.

After a knowledge transfer took place, $T = 1$, agent B's production cost in $t = 2$ is reduced by factor $0 < \alpha(T = 1) < 1$. When there was no transfer, agent B's production cost in $t = 2$ is multiplied by $\alpha(T = 0) = 1$. That is the value of α depends on T such that

$$0 < \alpha(T) \begin{cases} = 1 & \text{if } \; T = 0 \\ < 1 & \text{if } \; T = 1. \end{cases}$$

In $t = 2$, both agents address their assigned tasks which belong to the same project. Each agent decides to exert a high or low effort towards their task, i.e., agent A chooses $a \in \{0,1\}$ and agent B chooses $b \in \{0,1\}$. Choosing a high effort is costly for the agents. For agent A their task is costly with $\psi a \geq 0$ with $\psi > 0$. The task effort cost of agent B depends on whether a transfer took place in $t = 1$, such that effort costs are $\alpha(T)\theta b \geq 0$ with $\theta > 0$ and $0 < \alpha(T) \leq 1$. Whereas, agent A cannot directly gain from a knowledge transfer. The principal cannot verify the agents' task effort choice, however, the principal observes the verifiable joint outcome of the project, which A and B contribute to with their tasks. The outcome, Y, is binary such that the project is either successful, $Y = 1$, in which case the principal receives a revenue $R > 0$ or the project failed, $Y = 0$, then the principal receives nothing. The probability of a successful outcome depends on agents' effort choices in $t = 2$,

$$Pr[Y = 1|a, b] = p_{ab}.$$

The success probability satisfies $p_{11} > p_{10} \gtreqless p_{01} > p_{00} \geq 0$. Notice, that I do not make an assumption about whether the success probability is higher or lower when only agent A exerts a task effort compared to when only agent B exerts a task effort. Even though agent A shares knowledge with agent B this does not necessarily imply that agent A is more productive. It might as well be that agent B's task is more crucial for the project's success.

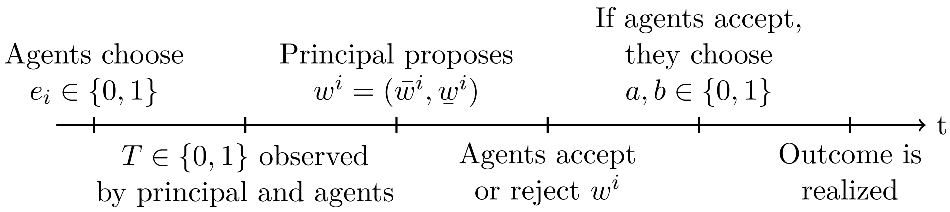


Figure 3.1: Timeline without commitment

The principal offers the agents a contract that depends on the project's outcome. In case of success, the agents receive a wage $\bar{w}^i$ for $i = A, B$. In case of a failure, the agents receive a wage $\underline{w}^i$. Hence, the principal offers a contract $w^i = (\bar{w}^i, \underline{w}^i)$ for $i = A, B$. The principal's objective is to maximize their expected profit.

In the analysis of this model, I look at two different contractual environments, that are determined by the role of commitment. When the principal has no commitment power, they can only propose a contract in the beginning of the second period. This implies that the principal cannot directly induce the agents on their action in the first period when they set up the contract. The timeline for the game in this contractual environment is shown in Figure 3.1. A situation like this can arise when the agents already work for the principal but are offered new contracts such that a contract is only provided in the second period.[66] This way the agents have the opportunity to exchange relevant knowledge before they sign a contract with the principal.

In this contractual environment, assuming that the principal is able to observe whether a transfer took place is a crucial assumption because the principal observes T before they offer a contract. Thus, they can select a contract accordingly.

In the second contractual environment, the principal can commit to a contract in the beginning of the first period. The principal uses long-term contracts to hire two agents who work on the same project and can transfer knowledge. The timeline for the game in this contractual environment is depicted in Figure 3.2. Notice that when

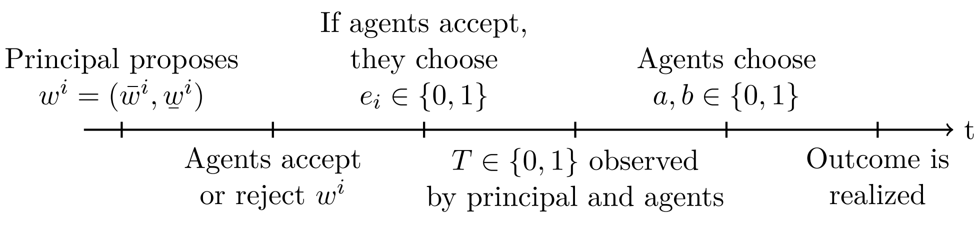


Figure 3.2: Timeline with commitment

the principal has commitment power it makes no difference whether they observe $T \in \{0,1\}$, because they cannot use the additional information as they commit to a contract ex ante. So in this environment, assuming that the principal can observe whether a transfer takes place is irrelevant.

[66]Alternatively, it could be that the principal hires two agents who already interacted with each other previously. During a job interview the principal can learn about their previous interactions.

To determine the first-best contract, suppose that both agents are induced to exert a task effort. Therefore, they are each paid an expected wage equal to their respective effort costs. From a social planner's perspective a knowledge transfer in the first period is efficient if

$$\theta > \alpha(1)\theta + 2\rho, \qquad (p_{11} - p_{10})R > \alpha(1)\theta + 2\rho,$$

$$(p_{11} - p_{01})R > \psi - \theta(1 - \alpha(1)) + 2\rho, \qquad (p_{11} - p_{00})R > \psi + \alpha(1)\theta + 2\rho.$$

I derive the conditions by comparing the expected pay-off for $T = 1$ and both agents exerting effort to the expected pay-offs for $T = 0$ and the different task efforts that can be implemented.[67] The first condition shows that the total costs from a knowledge transfer must be lower than B's task effort costs without a knowledge transfer, i.e., a knowledge transfer must be profitable. The following three conditions reveal that the gain from knowledge transfers and both agents exerting a task effort must be larger than the sum of the respective effort costs.

When solving this game for Nash equilibria, I focus on equilibria with a knowledge transfer. The principal's aim is to maximize their profit given that a transfer occurred. In the analysis of each contractual environment, I derive parameter restrictions under which a knowledge transfer is profitable for the principal.

3.3 No Commitment

In this section, the principal does not commit to a contract in the first period. They observe $T \in \{0, 1\}$ and only afterwards offer a contract to the agents. I focus on determining conditions under which knowledge transfer is a Nash equilibrium in the first period. Solving the game via backward induction, I start by defining the optimal contract in the second period given the outcome of the first period.

To that effect, I first characterize the respective contracts that minimize the principal's expected costs for inducing a given second-period effort profile. The principal has the option to induce both agents, only one agent or none of them to exert a task effort.

[67] Comparing it to the pay-offs without a transfer is more restrictive than the pay-offs with a knowledge transfer due to the transfer costs.

Lemma 3.1 *The contracts $w^i = (\bar{w}^i, \underline{w}^i)$ minimizing the principal's expected costs for a given second-period effort profile, (a, b), are*

(i) $w^A = \left(\frac{\psi}{p_{11}-p_{01}},\ 0\right)$ *and* $w^B = \left(\frac{\alpha(T)\theta}{p_{11}-p_{10}},\ 0\right)$ *to implement* $(1,1)$.

(ii) $w^A = (0,0)$ *and* $w^B = \left(\frac{\alpha(T)\theta}{p_{01}-p_{00}},\ 0\right)$ *to implement* $(0,1)$.

(iii) $w^A = \left(\frac{\psi}{p_{10}-p_{00}},\ 0\right)$ *and* $w^B = (0,0)$ *to implement* $(1,0)$.

To induce both agents to exert no task effort, a wage of zero in both states suffices.
Proof. *See Appendix.* ■

Lemma 3.1 presents the four different contracts for the possible effort profiles of A and B. In (i), (ii) and (iii) there is at least one agent who is induced to exert a high effort. In order to induce agents to exert a high effort, the principal pays them a positive rent when the project is successful and a wage of zero when it fails. Because of the agents' limited liability, the principal cannot use a negative wage to punish them. Instead, the limited liability condition is binding in case of failure and in case of success the principal pays a wage that more than compensates agents for their effort costs. Thus, inducing an agent to exert effort. In order to induce an agent to exert no effort, it is sufficient to pay them a zero wage for both outcomes, i.e., limited liability conditions are binding for both wages. Lemma 3.1 further shows that agent A's wages are independent of the first-period outcome for all second-period effort profiles. By contrast, agent B's rents depend on T since the value of factor $\alpha(T)$ is determined by the outcome of the first period. Hence, whenever the principal induces B to exert effort, the value of the rent is determined by the knowledge transfer. Suppose for example that $T = 1$, B's rent in part (i) and (ii) of Lemma 3.1 are multiplied by $0 < \alpha < 1$, such that B's productivity gain from a knowledge transfer is directly translated into lower rent and thus into a gain for the principal. Therefore, if it is optimal for the principal to induce agent B to exert a task effort, they can directly benefit from a knowledge transfer in the first period.

In Lemma 3.1, the second-period optimal contracts were established. Now given the outcome of the first period, we determine the optimal contracts.

Proposition 3.1 *For $T \in \{0,1\}$ it is optimal to implement second-period effort profile*

(i) $(1,1)$ *if R is sufficiently high, i.e., if the following three conditions hold*

$$R \geq \frac{p_{11}}{p_{11}-p_{01}}\left(\frac{\psi}{p_{11}-p_{01}} + \frac{\alpha(T)\theta}{p_{11}-p_{10}}\right) - \frac{p_{01}}{p_{11}-p_{01}}\frac{\alpha(T)\theta}{p_{01}-p_{00}}, \tag{3.1}$$

$$R \geq \frac{p_{11}}{p_{11}-p_{10}}\left(\frac{\psi}{p_{11}-p_{01}} + \frac{\alpha(T)\theta}{p_{11}-p_{10}}\right) - \frac{p_{10}}{p_{11}-p_{10}}\frac{\psi}{p_{10}-p_{00}}, \tag{3.2}$$

$$R \geq \frac{p_{11}}{p_{11}-p_{00}}\left(\frac{\psi}{p_{11}-p_{01}} + \frac{\alpha(T)\theta}{p_{11}-p_{10}}\right). \tag{3.3}$$

(ii) $(0,1)$ *if R takes on intermediate values, specifically under the following three conditions*

$$R \leq \frac{p_{11}}{p_{11}-p_{01}}\left(\frac{\psi}{p_{11}-p_{01}}+\frac{\alpha(T)\theta}{p_{11}-p_{10}}\right)-\frac{p_{01}}{p_{11}-p_{01}}\frac{\alpha(T)\theta}{p_{01}-p_{00}}, \tag{3.4}$$

$$R \geq \frac{p_{01}\alpha(T)\theta}{(p_{01}-p_{10})(p_{01}-p_{00})}-\frac{p_{10}\psi}{(p_{01}-p_{10})(p_{10}-p_{00})}, \tag{3.5}$$

$$R \geq \frac{p_{01}\alpha(T)\theta}{(p_{01}-p_{00})^2}. \tag{3.6}$$

(iii) $(1,0)$ *if R takes on intermediate values, specifically, under the following three conditions*

$$R \leq \frac{p_{11}}{p_{11}-p_{10}}\left(\frac{\psi}{p_{11}-p_{01}}+\frac{\alpha(T)\theta}{p_{11}-p_{10}}\right)-\frac{p_{10}}{p_{11}-p_{10}}\frac{\psi}{p_{10}-p_{00}}, \tag{3.7}$$

$$R \geq \frac{p_{10}\psi}{(p_{01}-p_{10})(p_{10}-p_{00})}-\frac{p_{01}\alpha(T)\theta}{(p_{01}-p_{10})(p_{01}-p_{00})}, \tag{3.8}$$

$$R \geq \frac{p_{10}\psi}{(p_{10}-p_{00})^2}. \tag{3.9}$$

(iv) $(0,0)$ *if R is sufficiently low, i.e., if the following three conditions hold*

$$R \leq \frac{p_{11}}{p_{11}-p_{00}}\left(\frac{\psi}{p_{11}-p_{01}}+\frac{\alpha(T)\theta}{p_{11}-p_{10}}\right), \tag{3.10}$$

$$R \leq \frac{p_{01}\alpha(T)\theta}{(p_{01}-p_{00})^2}, \tag{3.11}$$

$$R \leq \frac{p_{10}\psi}{(p_{10}-p_{00})^2}. \tag{3.12}$$

Proof. *See Appendix.* ■

Proposition 3.1 shows the optimality conditions of the different contracts. The conditions trade-off the principal's expected revenue and wage costs of the respective contracts derived in Lemma 3.1. Notice that the conditions are set up to include both first-period outcomes $T = 1$ and $T = 0$. For each contract there are three conditions because the principal's expected profit from implementing a specific effort profile is compared to the expected profit from each of the three remaining effort profiles.

The conditions in part (i) ensure that the principal's expected profit is largest when they implement effort profile $(1,1)$. If they are satisfied, the principal pays both agents a rent so that they both exert an effort, thus increasing the probability of success. This can only be profitable if the revenue is sufficiently high so that the principal can afford the wage costs. Conditions (3.2) and (3.3) are easier satisfied for $T = 1$, because B's rent is lower due to the productivity gain.

Contrary to part (i) is part (iv) since neither agent is induced to exert a task effort. The conditions guarantee that the expected profit is highest when the principal implements effort profile $(0, 0)$. This implies that the principal incurs no wage costs but also that there is a lower probability of success. If the revenue is low, the principal cannot afford to pay rents and thus not implementing effort from both agents is optimal. In opposition to (i), conditions in (iv) are more restrictive for $T = 1$ than for $T = 0$. Because B's rent becomes more affordable for the principal after a transfer occurred, the conditions are easier satisfied for $T = 0$.

If the revenue takes on intermediate values, it is profitable for the principal to induce one of the agents to exert an effort, however, they can only afford to pay one rent. Whether they induce agent A or agent B to work depends on the relation between p_{01} and p_{10} together with the task effort costs, ψ and $\alpha(T)\theta$. Part (ii) expresses the conditions for which it is optimal to offer a contract that induces only B to exert an effort. Part (iii) states the conditions for which it is optimal to only induce A to exert an effort. In both parts, the first condition indicates that R must not be too large otherwise the principal can afford to pay both agents a rent. The respective second and third conditions bound the revenue from below. While the respective last conditions make sure that the revenue is not too low so that it is profitable to pay one rent. The right-hand side of the respective second conditions are not necessarily positive.[68] Thus, it is ambiguous whether the conditions in (ii) and (iii) are easier satisfied for $T = 1$ or $T = 0$. Nevertheless, it is intuitive that the third restriction of (ii) is less restrictive for $T = 1$ since the principal pays a lower rent to agent B, whereas the first restriction of (iii) is more easily fulfilled for $T = 0$ because lowering B's rent makes it more affordable to induce agent B to exert an effort instead of agent A.

The analysis of the second period has shown that a productivity-enhancing knowledge transfer implies that the principal can induce agent B to exert an effort for a lower rent. Furthermore, depending on the parameter values, all available contracts can be optimal given the outcome of the first period.

Turning to the first period, I analyze the agents' transfer effort choice and focus on characterizing the conditions under which exerting a high transfer effort is a mutual best response for both. For the agents to engage in a knowledge transfer it has to pay off to incur the additional effort costs ρ. However, the principal cannot directly compensate them since they only offer them a contract in the beginning of the second period. Thus, given the optimal contract, their overall expected pay-off has to be larger for $T = 1$ than for $T = 0$. This already implies that agents only exert a transfer effort if they earn a rent, since otherwise their expected pay-off would be negative. Therefore, it must be optimal for the principal to induce effort profile $(1, 1)$

[68] For small ψ the right-hand side of (ii)'s second condition is positive and, therefore, negative for the second condition in (iii).

for $T = 1$, so that they pay each agent a positive rent to compensate them for the transfer effort costs.

Proposition 3.2 *Given the optimal contract implements second-period effort profile* $(1, 1)$ *for* $T = 1$*,*

- *and it is optimal to implement effort profile* $(0, 1)$ *for* $T = 0$*, a knowledge transfer is a subgame-perfect Nash equilibrium if*

$$\psi \geq \frac{p_{11} - p_{01}}{p_{01}} \rho \quad \text{and} \quad \alpha(1)\theta \geq \frac{p_{11} - p_{10}}{p_{10}} \left(\frac{p_{00}}{p_{01} - p_{00}} \theta + \rho \right).$$

- *and it is optimal to implement effort profile* $(1, 0)$ *for* $T = 0$*, a knowledge transfer is a subgame-perfect Nash equilibrium if*

$$\psi \geq \frac{(p_{11} - p_{01})(p_{10} - p_{00})}{p_{01}p_{10} - p_{11}p_{00}} \rho \quad \text{and} \quad \alpha(1)\theta \geq \frac{p_{11} - p_{10}}{p_{10}} \rho.$$

- *and it is optimal to implement effort profile* $(0, 0)$ *for* $T = 0$*, a knowledge transfer is a subgame-perfect Nash equilibrium if*

$$\psi \geq \frac{p_{11} - p_{01}}{p_{01}} \rho \quad \text{and} \quad \alpha(1)\theta \geq \frac{p_{11} - p_{10}}{p_{10}} \rho.$$

Proof. *See Appendix.* ■

Proposition 3.2 lists the three feasible cases in which, if the parameter conditions are satisfied, an agent's expected pay-off is higher when they engage in a knowledge transfer rather than refraining from it given that their co-worker also engages in a knowledge transfer. In all cases, it is the agents' mutual best response to choose a high transfer effort if the costs from the transfer effort is not too high or alternatively if the costs from the task effort, i.e., ψ for agent A and $\alpha(1)\theta$ for agent B, are sufficiently high. As a consequence, the agents' expected rent from the second period is large enough to compensate them for the costs from the transfer effort. In case of agent B, this implies that $\alpha(1)$ must not be too low and therefore the gain from the knowledge transfer must not be too high. Consequently, agent B's rent is sufficiently large. In all three cases, the agents gain from a transfer through a higher success probability for $T = 1$ than for $T = 0$ because the principal induces both agents to exert a task effort for $T = 1$. This is especially relevant for agent A in the first case and agent B in the second case because the respective agent is induced to exert a task effort for both $T = 1$ and $T = 0$. Thus, the conditions for these cases are more restrictive. The last case combines the less restrictive conditions for both agents, because both agents receive a wage of zero for $T = 0$. The agents do not exert a transfer effort given that it is optimal to implement the same effort profile for

$T = 1$ and $T = 0$. In that situation agents always receive a lower expected pay-off when they exert a transfer effort. Likewise, given that it is optimal to implement an effort profile that pays one or both agents a zero wage for $T = 1$, the agent(s) do not choose a high transfer effort since they would incur the additional costs ρ without compensation. Notice that for each case presented in Proposition 3.2 there exists another Nash equilibrium where agents choose no transfer effort such that no knowledge transfer occurs. However, under the given parameter restrictions on the effort costs, the Nash equilibrium where both agents exert a transfer effort yields a higher expected pay-off.

In terms of the optimal contract, all three cases have in common that for $T = 1$ it must be that the revenue is large enough so that it is optimal to induce both agents to exert a task effort and pay them a rent in the second period. The cases are distinct in the optimal contract for $T = 0$. In the first two cases, R must take intermediate values so that the principal can afford to induce one agent to exert a task effort, whereas in the last case the revenue must be low so that none of the agents receives a rent and exerts an effort. It follows that a knowledge transfer is profitable for the principal for R sufficiently large to induce effort profile $(1, 1)$ for $T = 1$ (cf. part (i) of Proposition 3.1). While simultaneously R cannot be too large for $T = 0$, so that the principal does not implement effort profile $(1, 1)$ for $T = 0$, as well. That is either restriction (3.4), (3.7) or (3.10) from Proposition 3.1 must hold for $T = 0$. In all three cases after the principal observed $T = 1$ the agents are induced to exert a second-period task effort. It is the agents' mutual best response to choose a transfer effort.

When the principal cannot commit to a contract but can observe the outcome of the first period, a knowledge transfer can be achieved if the principal's revenue takes an intermediate value where they can only pay both agents a rent if a knowledge transfer occurred. Through the transfer one of the agents becomes more productive in their task which in return leads to cost saving for the principal. It is less expensive to induce this agent to exert effort towards their task after a knowledge transfer. When the revenue fulfills the conditions in the paragraph above, the principal can credibly threaten to not pay both agents a rent if they do not observe a knowledge transfer. That is, in case the agents do not engage in a knowledge transfer one or both of them would forego a rent. Additionally, the probability for a success of the joint project decreases since the probability is highest when both agents exert a task effort. Therefore, both agents have something to loose when a knowledge transfer does not take place. When a principal receives a joint signal about the performance of both agents, e.g. agents work in a team, and they commit to a contract only after they observed a non-verifiable outcome, they can induce the agents to transfer knowledge even though they do not directly compensate them for the transfer costs. Due to the trade-off between rent extraction and efficiency, only a second-best allocation can be reached.

3.4 Commitment

In this section, the principal commits to a contract at the beginning of the first period. Therefore, it is irrelevant whether they observe T, since they cannot use the information for the contract they offer. Different from Section 3.3, in this section the principal determines whether to induce a knowledge transfer and chooses effort profiles for $T = 1$ and $T = 0$ at the beginning of the first period. I focus on contracts that induce a knowledge transfer while maximizing the principal's expected profit.

To that effect, I first characterize all contracts that induce a knowledge transfer by means of the effort profiles implemented for $T = 1$ and $T = 0$. Afterwards, I determine the optimal contract among these and define a condition under which the knowledge transfer is profitable for the principal.

Proposition 3.3 *The principal can only induce a knowledge transfer when they implement second-period effort profiles*

(i) $(1, 1)$ *for* $T = 1$ *and* $(1, 0)$ *or* $(0, 0)$ *for* $T = 0$ *or*

(ii) $(0, 1)$ *for* $T = 1$ *and* $(1, 0)$ *or* $(0, 0)$ *for* $T = 0$.

In the resulting Nash equilibria it is the agents' mutual best response to exert a knowledge transfer and at least agent B *exerts a task effort.*
Proof. *See Appendix.* ■

Proposition 3.3 describes all contracts that lead to a knowledge transfer in equilibrium. We learn that a knowledge transfer is only part of a Nash equilibrium if the principal induces both agents or only agent B to exert a task effort on-equilibrium path, i.e. for $T = 1$. Off-equilibrium path, the principal either implements second-period effort profile $(1, 0)$ or $(0, 0)$. By inducing effort profile $(1, 0)$ or $(0, 0)$ off-equilibrium path, in part (i) of Proposition 3.3 the principal provides the agents with an incentive to exert a transfer effort as mutual best response since the success probability is lower off-equilibrium path than the success probability on-equilibrium path. For part (ii), it is more complicated because previously I made no assumption on the relation between the success probabilities p_{10} and p_{01}, i.e., $p_{10} \gtreqless p_{01}$. However, the specific wages for part (ii) reveal that $p_{10} \geq p_{01}$ so that the limited liability constraints can be satisfied.[69] Therefore, the same argument of a lower success probability off-equilibrium path applies for part (ii) as well.

As in Section 3.3, in order to induce agents to exert task efforts the principal pays them a positive rent in case of success and a wage of zero in case of failure due to the limited liability conditions. However, different from Section 3.3, the principal also pays a rent to agent A even when they are not induced to exert a task effort on-equilibrium path, i.e. in part (ii) of Proposition 3.3. That is because the principal compensates agents not only for their task effort costs if applicable but also for their transfer effort costs.

[69] The specific wages of the contracts are derived and described in the Proof. See Appendix.

The contracts in Proposition 3.3 are the only ones that result in a Nash equilibrium with a knowledge transfer. For the contracts described in the proposition, firstly, this implies that the principal cannot induce a knowledge transfer when they implement the same second-period effort profiles on- and off-equilibrium path. If the principal were to implement the same second-period effort profile on- and off-equilibrium path, i.e., $(1,1)$ for part (i) and $(0,1)$ for part (ii), agent A would have no incentive to exert a transfer effort. In contrast to agent B, agent A cannot benefit from an increased productivity through the knowledge transfer and there is also no gain from a higher success probability. Instead agent A only incurs the additional effort costs $\rho > 0$ if they exert a transfer effort. Thus, a knowledge transfer is not a Nash equilibrium. Secondly, specific to part (i) of Proposition 3.3 a knowledge transfer in equilibrium cannot be reached when implementing effort profile $(0,1)$ off-equilibrium path. Similarly, for part (ii) a knowledge transfer in equilibrium cannot be reached for effort profile $(1,1)$ off-equilibrium path. The intuition for part (i) and (ii) is the same. In both cases, only agent A would be induced to choose a different task effort on- and off-equilibrium path. However, this is not feasible since A's performance in the second period is not directly affected by the outcome of the first period. Therefore, the principal cannot induce agent A to change their behavior based on the first-period outcome and implement the proposed effort profiles. Thirdly, the principal can also not induce a transfer when they implement effort profile $(1,0)$ or $(0,0)$ on-equilibrium path. Intuitively, the principal cannot benefit from a knowledge transfer if agent B whose productivity increases through the knowledge transfer is not induced to exert a task effort on-equilibrium path. The principal only incurs the costs from paying higher rents to induce a knowledge transfer without gaining from the productivity-increasing transfer since agent B does not exert an effort. Furthermore, for effort profile $(0,0)$ on-equilibrium path, all off-equilibrium path effort profiles lead to a success probability that is at least as high as on-equilibrium path.

To determine the optimal contract among the contracts characterized in Proposition 3.3, I assume for tractability that $p_{11} > 0$ and $p_{10},\ p_{01},\ p_{00} = 0$. This implies that a positive success probability is only reached when both agents exert a task effort. That is, for production both agents' effort is needed which is common in situations where two employees work on the same project.

Proposition 3.4 *Suppose that $p_{11} > 0$ and $p_{01},\ p_{10},\ p_{00} = 0$, the optimal contract, among the contracts that induce a knowledge transfer in equilibrium, implements second-period effort profile (1,1) for $T = 1$ and $(0,0)$ for $T = 0$ with*

$$w^{A*} = \left(\frac{\psi + \rho}{p_{11}},\ 0\right) \quad \textit{and} \quad w^{B*} = \left(\frac{\alpha(1)\theta + \rho}{p_{11}},\ 0\right).$$

The contract achieves the first-best allocation.

Proof. *See Appendix.* ■

The principal induces both agents to exert task effort on-equilibrium path without paying them a rent. Instead they only compensate agents for their participation. It is the agents' mutual best response to exert a transfer effort. Thus, the principal achieves the first-best allocation. Under the simplifying assumption, any second-period effort profile where only one agent is induced to exert effort can neither be implemented on- nor off-equilibrium path. The reason is that they incur their respective effort costs, however, the success probability remains zero if they are the only one exerting a task effort, so that they do not benefit from the exerted effort. Therefore, the Nash equilibrium in Proposition 3.4 is unique.

The principal profits from inducing a knowledge transfer if $\theta > \alpha(1)\theta + 2\rho$ and $p_{11}R > \psi + \alpha(1)\theta + 2\rho$. The first condition states that the total costs from a knowledge transfer must be below the costs without a knowledge transfer. This condition is equivalent to the condition derived in Section 3.2 for the first-best allocation. The second condition simply specifies that the expected revenue from the optimal contract must be larger than the costs. This condition corresponds to the last condition derived for the first-best allocation.[70]

The first-best outcome can also be reached for $p_{11} > p_{10} \gtreqless p_{01} > p_{00} = 0$. In equilibrium the agents engage in a knowledge transfer and both exert a task effort, while off-equilibrium path the principal implements effort profile $(0, 0)$. The principal does not pay the agents a rent as long as $\theta \, \frac{p_{11}}{p_{01}} \geq \alpha(1)\theta + \rho$ and $\frac{p_{11}-p_{10}}{p_{10}} \, \psi \geq \rho$, i.e., as long as the costs from a transfer are below the costs without a transfer. The assumption on the success probabilities is less restrictive, since it is only presumed that if both agents do not exert a task effort the project fails with certainty. However, under this assumption the Nash equilibrium is not unique and deriving the conditions under which the contract is optimal and when the transfer is profitable are not tractable.

When the principal has commitment power, they can commit to compensating the agents for their transfer costs and induce a knowledge transfer in equilibrium. In order to do so the principal must at least offer agent B an incentive to exert a task effort in the second-period. As shown in Proposition 3.3, when the principal induces a knowledge transfer, the agents gain from a higher success probability on-equilibrium path compared to off-equilibrium path. This is similar to the case without commitment: Under certain conditions regarding the revenue, the principal provides an incentive for a transfer by implementing effort profile $(1, 1)$ only after they observed a transfer. Thus, agents are faced with a lower success probability when they did not engage in a knowledge transfer. What is different between the two contractual frameworks, however, is that the principal always pays agents a rent when they induce a knowledge transfer under commitment. As a result, the first-best allocation can be reached when the principal has commitment power.

[70] I do not need to compare the expected profit from the optimal contract to a contract where second-period effort profile $(1, 0)$ or $(0, 1)$ is implemented since they cannot be achieved under the simplifying assumption.

3.5 Value of Commitment

This section proceeds on the assumption that a principal wants to induce a productivity-increasing knowledge transfer between agents. When looking at the contracts in Sections 3.3 and 3.4, the structures differ when the principal has commitment power versus when they do not. When the principal has no commitment power, they offer a contract at the beginning of the second period after they observed $T \in \{0, 1\}$. Thus, they can implement a different effort profile for $T = 1$ and $T = 0$. Given it is optimal for the principal to induce effort profile $(1, 1)$ after $T = 1$ and a different effort profile after $T = 0$, under certain restrictions (cf. Proposition 3.2) it is the agents' mutual best response to exert a transfer effort. Hence, without commitment a transfer can only be realized in equilibrium when the principal implements effort profile $(1, 1)$ after $T = 1$ and a different effort profile after $T = 0$. When the principal has commitment power, they offer a contract at the beginning of the first period without observing T. It implements an effort profile for $T = 1$ and $T = 0$ and can provide an incentive to exert a transfer effort as a mutual best response. The contracts that lead to a knowledge transfer in equilibrium implement effort profile $(1, 1)$ or $(0, 1)$ for $T = 1$ and respectively a different contract for $T = 0$ (cf. Proposition 3.3).

Commitment can provide a value to the principal in that they can also induce effort profile $(0, 1)$ for $T = 1$ and still reach a Nash equilibrium with a knowledge transfer. This proves to be valuable in situations where the revenue is so low that it is not optimal for the principal to pay two rents and induce effort profile $(1, 1)$ without commitment (cf. Proposition 3.1), while the revenue is still large enough for a profitable implementation of effort profile $(0, 1)$ and $T = 1$ with commitment.

Furthermore, under the simplifying assumption that $p_{11} > 0$ and $p_{01},\ p_{10},\ p_{00} = 0$, I found that the optimal, knowledge-transfer inducing contract achieves the first-best allocation. Using the same assumption when the principal has no commitment power, they can implement effort profiles $(1, 1)$ and $(0, 0)$ with wages that exactly satisfy the agents' participation constraints, so that there is no rent for the agents. However, even if it is optimal to implement effort profile $(1, 1)$ after $T = 1$ and effort profile $(0, 0)$ after $T = 0$, this does not result in a knowledge transfer as Nash equilibrium. Because the agents do not receive a rent, they have no incentive to incur the transfer costs to exert a transfer effort. Particularly, since B's wage is lowered through a knowledge transfer. Therefore, the first-best allocation cannot be reached. Without commitment power, a transfer can only be a Nash equilibrium, if agents are also effective when they are the only one to exert a task effort.

On the other hand, having commitment power is not always better though. For high transfer costs, ρ, not having commitment power can be more profitable since the principal does not internalize the transfer effort costs in their optimization problem. Thus, for specific parameter constellations and ceteris paribus, the expected profit is higher without commitment than with commitment. In conclusion, commitment power is not a value in itself. For certain parameter values a principal may be better off if they have no commitment power.

3.6 Conclusion

In this chapter, I examine the incentive structure behind knowledge transfer a principal's options to induce such transfer between workers. I develop a dynamic principal-agent model with a standard moral hazard problem with respect to the agents' effort and add a stage for a non-verifiable knowledge transfer between agents. A principal hires two risk-neutral and wealth-constrained agents to exert non-verifiable effort towards a task for each agent. Before the agents address their tasks they can choose to transfer knowledge which increases the productivity of the knowledge receiver. The knowledge transfer is one-sided and costly for sender and receiver. I explore the principal's options to induce a knowledge transfer when they do not have commitment power and when they have commitment power.

In the model specification when the principal cannot commit to a contract at the beginning of the game, they pay the agents a rent for their task effort. A knowledge transfer which increases the productivity of one agent leads to a decrease of their rent. Thus, a knowledge transfer can be cost-saving for the principal. I find that for sufficiently low transfer costs a knowledge transfer is an equilibrium given that it is optimal for the principal to induce both agents to exert a task effort only after the principal observed a non-verifiable transfer. Hence, it must be profitable to pay two rents only after a knowledge transfer occurred and it must be too expensive without a knowledge transfer. As a consequence, the principal can credibly threaten to not pay either agent a rent if they do not observe a knowledge transfer. Thus, one agent foregoes their rent while they are both affected by a lower success probability if they do not transfer knowledge.

In the alternative model specification when the principal commits to a contract at the beginning of the first period, the contracts are characterized by the effort profiles that are implemented for $T = 1$ and $T = 0$ and the principal either induces agents to transfer knowledge or not. The principal pays agents a rent for their transfer and task effort(s). In contrast to the environment without commitment, this means that they also pay a rent if an agent does not exert a task effort. I find that a Nash equilibrium with a knowledge transfer induces at least agent B, the receiver of knowledge, to exert a task effort on-equilibrium path. Off-equilibrium path, the principal must implement an effort profile that leads to a lower success probability. This notion is similar to the environment without commitment. With commitment, the first-best allocation can be achieved under two different parameter restrictions regarding the success probabilities. The first-best allocation is only attained when the principal has commitment power. However, in this model, it is not clear that commitment is always better than no commitment. For high transfer costs, when the principal induces a transfer, having no commitment power can be at least as good as commitment in terms of the expected profits. That is, because the principal pays agents a rent for their transfer effort even if they do not exert a task effort. Without commitment, the principal saves the cost from compensating the agents for their transfer effort.

This chapter contributes to the literature as it focuses on knowledge transfer as a specific form of cooperation between workers. A main driver in my model is the joint signal on the agents' performance. Since the success probability depends on both agents' task effort, it can provide them with an incentive to engage in a one-sided knowledge transfer. In practice, however, workers exchange knowledge not only within their team but also across teams. It is one of management's biggest challenges to ensure that knowledge, which already exists in companies, is used and distributed. Therefore, it would be interesting for future research to consider a model on knowledge transfer where agents do not work in a team and where there is no joint signal on agents' performance. Can they be induced with monetary rewards to share knowledge? Is that so even if it is a one-sided knowledge transfer? Another starting point for future research is to take this model and study how the results change for a two-sided knowledge transfer. The agents might have an intrinsic motivation to transfer knowledge under these circumstances. Therefore, a principal may be able to induce a knowledge transfer with lower-powered incentives. What role does the crowding-out effect play in such a setting?

3.A Appendix: Proofs

Proof of Lemma 3.1

(i) The principal's optimization problem given they implement effort profile $(1, 1)$ is

$$\min_{\bar{w}^i, \underline{w}^i} p_{11}(\bar{w}^A + \bar{w}^B) + (1 - p_{11})(\underline{w}^A + \underline{w}^B)$$

subject to

$$p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi \geq p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A \qquad (IC^A)$$

$$p_{11}\bar{w}^B + (1 - p_{11})\underline{w}^B - \alpha(T)\theta \geq p_{10}\bar{w}^B + (1 - p_{10})\underline{w}^B \qquad (IC^B)$$

$$p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi \geq 0 \qquad (PC^A)$$

$$p_{11}\bar{w}^B + (1 - p_{11})\underline{w}^B - \alpha(T)\theta \geq 0 \qquad (PC^B)$$

$$\bar{w}^A, \ \bar{w}^B, \ \underline{w}^A, \ \underline{w}^B \geq 0 \qquad \text{(LL)}$$

The participation constraints of both agents are implied by the respective incentive constraints. Therefore, the participation constraints are slack. The limited liability constraint is binding in a low state such that $\underline{w}^A, \underline{w}^B = 0$. Substituting this result into the agents' incentive constraints indicates the optimal wages in a high state, i.e.,

$$\bar{w}^A = \frac{\psi}{p_{11} - p_{01}} \qquad \bar{w}^B = \frac{\alpha(T)\theta}{p_{11} - p_{10}}.$$

(ii) & (iii) The principal's optimization problems given they implement effort profile $(0, 1)$ or $(1, 0)$, respectively are:

$$\min_{\bar{w}^i, \underline{w}^i} p_{01}(\bar{w}^A + \bar{w}^B) + (1 - p_{01})(\underline{w}^A + \underline{w}^B)$$

subject to

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A \geq p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi \qquad (IC^A)$$

$$p_{01}\bar{w}^B + (1 - p_{01})\underline{w}^B - \alpha(T)\theta \geq p_{00}\bar{w}^B + (1 - p_{00})\underline{w}^B \qquad (IC^B)$$

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A \geq 0 \qquad (PC^A)$$

$$p_{01}\bar{w}^B + (1 - p_{01})\underline{w}^B - \alpha(T)\theta \geq 0 \qquad (PC^B)$$

$$\bar{w}^A, \ \bar{w}^B, \ \underline{w}^A, \ \underline{w}^B \geq 0 \qquad \text{(LL)}$$

and

$$\min_{\bar{w}^i, \underline{w}^i} p_{10}(\bar{w}^A + \bar{w}^B) + (1 - p_{10})(\underline{w}^A + \underline{w}^B) \tag{3.13}$$

subject to

$$p_{10}\bar{w}^A + (1 - p_{10})\underline{w}^A - \psi \geq p_{00}\bar{w}^A + (1 - p_{00})\underline{w}^A \qquad (IC^A)$$

$$p_{10}\bar{w}^B + (1 - p_{10})\underline{w}^B \geq p_{11}\bar{w}^B + (1 - p_{11})\underline{w}^B - \alpha(T)\theta \qquad (IC^B)$$

$$p_{10}\bar{w}^A + (1 - p_{10})\underline{w}^A - \psi \geq 0 \qquad (PC^A)$$

$$p_{10}\bar{w}^B + (1 - p_{10})\underline{w}^B \geq 0 \qquad (PC^B)$$

$$\bar{w}^A,\ \bar{w}^B,\ \underline{w}^A,\ \underline{w}^B \geq 0 \qquad \text{(LL)}$$

The proofs of (ii) and (iii) of Lemma 3.1 are similar to each other. In (ii) agent B is the only one who is induced to choose a high task effort while in (iii) it is agent A. The respective other agent is incentivized to choose a low task effort. For that agent their limited liability constraints are binding, such that in (ii) $\bar{w}^A, \underline{w}^A = 0$, while in (iii) $\bar{w}^B, \underline{w}^B = 0$.

On the other hand, for the agent who is induced to choose a high effort in the respective Lemma, the proof is the same as in part (i) of Lemma 3.1. The participation constraint of that agent is implied by the incentive constraint which is binding. While the limited liability condition binds in the low state. This indicates the optimal wages.

Last but not least, the principal's optimization problem when implementing effort profile $(0, 0)$ is given by

$$\min_{\bar{w}^i, \underline{w}^i} p_{00}(\bar{w}^A + \bar{w}^B) + (1 - p_{00})(\underline{w}^A + \underline{w}^B) \tag{3.14}$$

subject to

$$p_{00}\bar{w}^A + (1 - p_{00})\underline{w}^A \geq p_{10}\bar{w}^A + (1 - p_{10})\underline{w}^A - \psi \qquad (IC^A)$$

$$p_{00}\bar{w}^B + (1 - p_{00})\underline{w}^B \geq p_{01}\bar{w}^B + (1 - p_{01})\underline{w}^B - \alpha(T)\theta \qquad (IC^B)$$

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A \geq 0 \qquad (PC^A)$$

$$p_{00}\bar{w}^B + (1 - p_{00})\underline{w}^B \geq 0 \qquad (PC^B)$$

$$\bar{w}^A,\ \bar{w}^B,\ \underline{w}^A,\ \underline{w}^B \geq 0 \qquad \text{(LL)}$$

The incentive constraints imply that it is A's and B's mutual best response to choose a low effort given the other agent's action. The limited liability constraints are binding for both agents revealing the wages.

Proof of Proposition 3.1

The principal's expected profit for contract (i) of Lemma 3.1 is

$$\Pi(1,1) = p_{11}\left(R - \frac{\psi}{p_{11}-p_{01}} - \frac{\alpha(T)\theta}{p_{11}-p_{10}}\right).$$

It is higher for $T = 1$ than for $T = 0$ due to the productivity gain.

The principal's expected profit for contract (ii) of Lemma 3.1 is given by

$$\Pi(0,1) = p_{01}\left(R - \frac{\alpha(T)\theta}{p_{01}-p_{00}}\right).$$

It is again higher for $T = 1$ than for $T = 0$.

The principal's expected profit for contract (iii) of Lemma 3.1 is

$$\Pi(1,0) = p_{10}\left(R - \frac{\psi}{p_{10}-p_{00}}\right),$$

which is the same for any T.

The principal's expected profit when they induce both agents to not exert an effort is equivalent to their expected revenue $p_{00}R$.

The three restrictions in (i) of Proposition 3.1 depict the following three inequalities

$$\Pi(1,1) \geq \Pi(0,1) \qquad \Pi(1,1) \geq \Pi(1,0) \qquad \Pi(1,1) \geq \Pi(0,0).$$

Parts (ii) to (iv) of Proposition 3.1 follow the same pattern revealing the restrictions under which each effort profile gives the largest expected profit.

Proof of Proposition 3.2

It is optimal for the agents to choose $e^{A^*} = e^{B^*} = 1$ if each their overall expected pay-offs are higher than if they choose differently, given the optimal contracts. The expected pay-offs consider the wage and effort costs from the second-period and if applicable the effort costs from the first period. Thus, the conditions in Proposition 3.2 are derived by comparing the agents' expected pay-offs if they choose to exert a transfer effort given the optimal contract for $T = 1$ to the expected pay-off if they choose to not exert a transfer effort given the optimal contract for $T = 0$. In the first case of the Proposition for agent A this means that

$$p_{11}\frac{\psi}{p_{11}-p_{01}} - \psi - \rho \geq 0$$

must hold so that they choose a positive transfer effort. Analogous for agent B it must hold that

$$p_{11}\frac{\alpha(1)\theta}{p_{11}-p_{10}} - \alpha(1)\theta - \rho \geq p_{01}\frac{\theta}{p_{01}-p_{00}} - \theta.$$

In the second case for agent A it must hold that

$$p_{11}\frac{\psi}{p_{11}-p_{01}} - \psi - \rho \geq p_{10}\frac{\psi}{p_{10}-p_{00}} - \psi,$$

while for agent B it must be that

$$p_{11}\frac{\alpha(1)\theta}{p_{11}-p_{10}} - \alpha(1)\theta - \rho \geq 0.$$

The final case combines constraints from the first two cases for agent A and B, i.e.,

$$p_{11}\frac{\psi}{p_{11}-p_{01}} - \psi - \rho \geq 0$$

and

$$p_{11}\frac{\alpha(1)\theta}{p_{11}-p_{10}} - \alpha(1)\theta - \rho \geq 0$$

must be satisfied for A and B, respectively.

Now, I show that there exist no other cases where both agents choose to exert a high transfer effort. First, assume towards a contradiction that the principal offers a contract that induces effort profile $(1,1)$ for any T. In this case, the agents receive the same expected wage for $T=1$ and for $T=0$. However, they incur the additional effort costs $\rho > 0$ for $T=1$. Hence, it is never optimal to choose $e^A, e^B = 1$. The proof is the same for any other contract that is offered independent of T. Second, assume that for $T=1$ the principal offers a contract where one agent receives a zero wage in both states, that is in this case the principal implements second-period effort profile $(1,0)$, $(0,1)$ or $(0,0)$. That agent's expected pay-off is $-\rho < 0$ if they choose a high transfer effort. Therefore, they are always better off by choosing a low transfer effort, since their expected pay-off is at least non-negative. Hence, choosing to exert a transfer effort is only a mutual best response when both agents receive a positive rent.

Proof of Proposition 3.3

(i) The principal induces a knowledge transfer and effort profiles $(1,1)$ for $T=1$ and $(1,0)$ or $(0,0)$ for $T=0$. Thus, the first optimization problem is given by

$$\min_{w^A, w^B \geq 0} p_{11}(\bar{w}^A + \bar{w}^B) + (1-p_{11})(\underline{w}^A + \underline{w}^B)$$

subject to

$$\underline{w}^A, \underline{w}^B, \bar{w}^A, \bar{w}^B \geq 0 \tag{LL}$$

$$p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi - \rho \geq 0 \tag{PC^A}$$

$$p_{11}\bar{w}^B + (1-p_{11})\underline{w}^B - \alpha(1)\theta - \rho \geq 0 \tag{PC^B}$$

$$p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi \geq p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A \tag{3.15}$$

$$p_{11}\bar{w}^B + (1-p_{11})\underline{w}^B - \alpha(1)\theta \geq p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B \tag{3.16}$$

$$p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi \geq p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A \tag{3.17}$$

$$p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B \geq p_{11}\bar{w}^B + (1-p_{11})\underline{w}^B - \theta \tag{3.18}$$

$$p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi - \rho \geq p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi \tag{3.19}$$

$$p_{11}\bar{w}^B + (1-p_{11})\underline{w}^B - \alpha(1)\theta - \rho \geq p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B \tag{3.20}$$

Second-period incentive constraints (3.15) and (3.16) ensure that given $T = 1$, agent A's (agent B's) best response to agent B's (A's) action is to choose a high effort. Second-period incentive constraints (3.17) and (3.18) ensure that given $T = 0$ it is A's (B's) best response to choose a high (low) effort. For agent B's second-period incentive constraints, (3.16) and (3.18), to be satisfied at the same time, it must be that $\alpha(1) \leq 1$ which is true by the definition of $\alpha(T)$. First-period incentive constraints (3.19) and (3.20) reflect that it is both agents mutual best response to choose a high transfer effort.

The participation constraints for both agents are not binding because they are implied by the respective first-period incentive constraints, (3.19) and (3.20), and limited liability conditions on $\underline{w}^i$. Therefore, the participation constraints are slack and limited liability constraints for $\underline{w}^i \forall i = A, B$ are binding.

For agent A it holds that any wage in case of success that satisfies

$$\bar{w}^A \geq \frac{\psi}{p_{11} - p_{01}}, \frac{\psi}{p_{10} - p_{00}}, \frac{\rho}{p_{11} - p_{10}},$$

fulfills all three incentive constraints, (3.15), (3.17), (3.19). That means it depends on the parameter constellation which incentive constraint is binding. The second-period incentive constraint, (3.15), binds if

$$\frac{\psi}{p_{11} - p_{01}} \geq \frac{\psi}{p_{10} - p_{00}}, \frac{\rho}{p_{11} - p_{10}}.$$

The second-period incentive constraint, (3.17), binds if

$$\frac{\psi}{p_{10} - p_{00}} \geq \frac{\psi}{p_{11} - p_{01}}, \frac{\rho}{p_{11} - p_{10}}.$$

Last but not least, the first-period incentive constraint binds if

$$\frac{\rho}{p_{11}-p_{10}} \geq \frac{\psi}{p_{11}-p_{01}}, \ \frac{\psi}{p_{10}-p_{00}}.$$

Agent B's second-period incentive constraint given $T=1$, (3.16), is implied by their first-period incentive constraint, (3.20), as the right-hand sides are equal while the left-hand side of (3.20) is strictly smaller than the right-hand side of (3.16), since $\rho > 0$. Therefore, whenever (3.20) is satisfied (3.16) also holds, such that (3.16) is not binding. Any wage that satisfies (3.18) and (3.20), i.e.,

$$\frac{\theta}{p_{11}-p_{10}} \geq \bar{w}^B \geq \frac{\alpha\theta+\rho}{p_{11}-p_{10}}$$

fulfills all incentive constraints. Thus, the sufficient constraints, (3.18) and (3.20) are satisfied for the same parameter constellation. However, (3.20) indicates the lower wage of the two and therefore it is binding.Agent B's second-period incentive constraint given $T=0$ represents an upper bound for $\bar{w}^B$, such that $\theta \geq \alpha(1)\theta+\rho$ is a necessary condition for B's wage scheme.

The wages that implement effort profiles $(1,1)$ for $T=1$ and $(1,0)$ for $T=0$ are given by

$$\bar{w}^A = \begin{cases} \frac{\psi}{p_{11}-p_{01}} & \text{if } \psi \frac{p_{11}-p_{10}}{p_{11}-p_{01}} \geq \rho \ \& \ p_{10}+p_{01} \geq p_{11}+p_{00} \\ \frac{\psi}{p_{10}-p_{00}} & \text{if } \psi \frac{p_{11}-p_{10}}{p_{10}-p_{00}} \geq \rho \ \& \ p_{11}+p_{00} \geq p_{10}+p_{01} \\ \frac{\rho}{p_{11}-p_{10}} & \text{if } \psi \frac{p_{11}-p_{10}}{p_{10}-p_{00}}, \ \psi \frac{p_{11}-p_{10}}{p_{11}-p_{01}} \leq \rho, \end{cases}$$

$$\underline{w}^A = 0 \quad \textit{and}$$

$$\bar{w}^B = \frac{\alpha(1)\theta+\rho}{p_{11}-p_{10}} \ \text{ for } \ \theta \geq \alpha(1)\theta+\rho, \qquad \underline{w}^B = 0.$$

For small ρ, that is for low transfer costs, it suffices to pay agent A a rent based on their task effort costs to induce a high task effort and a high transfer effort. On the other hand, for large ρ, that is for high transfer costs, the principal pays A a rent that is based on the transfer costs to induce a high effort in both periods. Agent B's wage $\bar{w}^B$ is determined by their first-period incentive constraint. To induce agent B to exert a transfer effort but a task effort only for $T=1$, they must earn a rent based on the sum of their effort costs given $T=1$. This wage satisfies all incentive constraints, if the effort costs without a transfer are at least as high as the effort costs with a transfer. That is the productivity gain from a knowledge transfer offsets the additional transfer costs. The productivity gain is translated into a rent lowered by $\alpha(1)$, such that B does not have an incentive to choose a high task effort given $T=0$.

The optimization problem for effort profiles $(1,1)$ for $T=1$ and $(0,0)$ for $T=0$ is given by

$$\min_{w^A,w^B\geq 0} p_{11}(\bar{w}^A+\bar{w}^B)+(1-p_{11})(\underline{w}^A+\underline{w}^B)$$

subject to

$$p_{11}\bar{w}^A+(1-p_{11})\underline{w}^A-\psi-\rho\geq 0 \tag{PC^A}$$

$$p_{11}\bar{w}^B+(1-p_{11})\underline{w}^B-\alpha(1)\theta-\rho\geq 0 \tag{PC^B}$$

$$\bar{w}^A,\underline{w}^A,\bar{w}^B,\underline{w}^B\geq 0 \tag{LL}$$

$$p_{00}\bar{w}^A+(1-p_{00})\underline{w}^A\geq p_{10}\bar{w}^A+(1-p_{10})\underline{w}^A-\psi \tag{3.21}$$

$$p_{00}\bar{w}^B+(1-p_{00})\underline{w}^B\geq p_{01}\bar{w}^B+(1-p_{01})\underline{w}^B-\theta \tag{3.22}$$

$$p_{11}\bar{w}^A+(1-p_{11})\underline{w}^A-\psi-\rho\geq p_{00}\bar{w}^A+(1-p_{00})\underline{w}^A \tag{3.23}$$

$$p_{11}\bar{w}^B+(1-p_{11})\underline{w}^B-\alpha(1)\theta-\rho\geq p_{00}\bar{w}^B+(1-p_{00})\underline{w}^B \tag{3.24}$$

and (3.15), (3.16).

Second-period incentive constraints for $T=1$ are the same as in part (i). Second-period incentive constraints for $T=0$, (3.21) and (3.22), ensure that A's and B's mutual best response is to choose a low effort. The first-period incentive constraints, (3.23) and (3.24), ensure that it is their mutual best response to choose a high transfer effort.

Both agents' participation constraints are not binding because they are implied by the respective first-period incentive constraints, (3.23) and (3.24) and limited liability constraints on $\underline{w}^i$. Therefore, the participation constraints are slack and limited liability conditions for $\underline{w}^{i*}=0\ \forall i=A,B$.

For agent A it holds that any wage $\bar{w}^A\geq 0$ that satisfies

$$\frac{\psi}{p_{10}-p_{00}}\geq\bar{w}^A\geq\frac{\psi}{p_{11}-p_{01}},\ \frac{\psi+\rho}{p_{11}-p_{00}}$$

fulfills all three necessary incentive constraints. That means it depends on the parameter constellation which incentive constraint is binding. The second-period incentive constraint, (3.15), binds if

$$\frac{\psi}{p_{10}-p_{00}}\geq\frac{\psi}{p_{11}-p_{01}}\ \text{ and }\ \frac{\psi}{p_{11}-p_{01}}\geq\frac{\psi+\rho}{p_{11}-p_{00}}.$$

The first-period incentive constraint, (3.23), binds if

$$\frac{\psi}{p_{10}-p_{00}} \geq \frac{\psi+\rho}{p_{11}-p_{00}} \quad \text{and} \quad \frac{\psi+\rho}{p_{11}-p_{00}} \geq \frac{\psi}{p_{11}-p_{01}}.$$

Finally, second-period incentive constraint, (3.21), binds if

$$\frac{\psi}{p_{10}-p_{00}} \geq \frac{\psi}{p_{11}-p_{01}}, \frac{\psi+\rho}{p_{11}-p_{00}}.$$

For agent B it holds that any wage $\bar{w}^B \geq 0$ that satisfies

$$\frac{\theta}{p_{01}-p_{00}} \geq \bar{w}^B \geq \frac{\alpha(1)\theta}{p_{11}-p_{10}}, \frac{\alpha(1)\theta+\rho}{p_{11}-p_{00}}$$

fulfills all three necessary incentive constraints. That means it depends on the parameter constellation which incentive constraint is binding. The second-period incentive constraint, (3.16) binds if

$$\frac{\alpha(1)\theta}{p_{11}-p_{10}} \geq \frac{\alpha(1)\theta+\rho}{p_{11}-p_{00}} \quad \text{and} \quad \frac{\theta}{p_{01}-p_{00}} \geq \frac{\alpha(1)\theta}{p_{11}-p_{10}}.$$

The first-period incentive constraint, (3.24), binds if

$$\frac{\alpha(1)\theta}{p_{11}-p_{10}} \leq \frac{\alpha(1)\theta+\rho}{p_{11}-p_{00}} \quad \text{and} \quad \frac{\theta}{p_{01}-p_{00}} \geq \frac{\alpha(1)\theta+\rho}{p_{11}-p_{00}}.$$

The other second-period incentive constraint, (3.22), binds if

$$\frac{\theta}{p_{01}-p_{00}} \geq \frac{\alpha(1)\theta}{p_{11}-p_{10}}, \frac{\alpha(1)\theta+\rho}{p_{11}-p_{00}}.$$

The wages that implement effort profiles $(1,1)$ for $T=1$ and $(0,0)$ for $T=0$ are given by

$$\bar{w}^A = \begin{cases} \frac{\psi}{p_{10}-p_{00}} & \text{if } \psi\ \frac{p_{11}-p_{10}}{p_{10}-p_{00}} \geq \rho \ \&\ p_{11}+p_{00} \geq p_{01}+p_{10} \\ \frac{\psi}{p_{11}-p_{01}} & \text{if } \psi\ \frac{p_{01}-p_{00}}{p_{11}-p_{01}} \geq \rho \ \&\ p_{11}+p_{00} \geq p_{01}+p_{10} \\ \frac{\psi+\rho}{p_{11}-p_{00}} & \text{if } \psi\ \frac{p_{11}-p_{10}}{p_{10}-p_{00}} \geq \rho \geq \psi\ \frac{p_{01}-p_{00}}{p_{11}-p_{01}}, \end{cases}$$

$\underline{w}^A = 0$ *and*

$$\bar{w}^B = \begin{cases} \frac{\theta}{p_{01}-p_{00}} & \text{if } \theta\ \frac{p_{11}-p_{00}}{p_{01}-p_{00}} \geq \alpha(1)\theta+\rho \ \&\ \frac{p_{11}-p_{10}}{p_{01}-p_{00}} \geq \alpha(1) \\ \frac{\alpha(1)\theta}{p_{11}-p_{10}} & \text{if } \alpha(1)\theta\ \frac{p_{10}-p_{00}}{p_{11}-p_{10}} \geq \rho \ \&\ \frac{p_{11}-p_{10}}{p_{01}-p_{00}} \geq \alpha(1) \\ \frac{\alpha(1)\theta+\rho}{p_{11}-p_{00}} & \text{if } \theta\ \frac{p_{11}-p_{00}}{p_{01}-p_{00}} \geq \alpha(1)\theta+\rho \ \&\ \alpha(1)\theta\ \frac{p_{10}-p_{00}}{p_{11}-p_{10}} \leq \rho, \end{cases}$$

$\underline{w}^B = 0.$

Similar to above, A's rent for $\bar{w}^A$ is based on their task effort cost, ψ, if the transfer costs are low. For small ρ this also induces them to choose a high transfer effort. If ρ takes intermediate values, A gets a rent based on the sum of their effort costs of the first and second period. Agent B's wage $\bar{w}^B$ is determined by their three incentive constraints. When θ is larger than the sum of the effort costs and there is a large gain from a transfer, i.e., $\alpha(1)$ is small, the principal pays B a rent based on θ. This ensures that agent B chooses a high effort in both periods. However, when the gain from a transfer is still high but $\alpha(1)\theta$ is also larger than ρ, the rent is based on $\alpha(1)\theta$. Finally, the principal pays B a rent based on the sum of the first and second period effort costs, when ρ is large but the sum of the effort costs is still smaller than the effort costs without a transfer. Agent B, thus only has an incentive to choose a task effort given $T = 1$.

(ii) The principal induces a knowledge transfer and effort profiles $(0, 1)$ for $T = 1$ and $(1, 0)$ or $(0, 0)$ for $T = 0$. Thus, the first optimization problem is given by

$$\min_{w^A, w^B} p_{01}(\bar{w}^A + \bar{w}^B) + (1 - p_{01})(\underline{w}^A + \underline{w}^B)$$

subject to

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A - \rho \geq 0 \tag{PC^A}$$

$$p_{01}\bar{w}^B + (1 - p_{01})\underline{w}^B - \alpha(1)\theta - \rho \geq 0 \tag{PC^B}$$

$$\bar{w}^A, \underline{w}^A, \bar{w}^B, \underline{w}^B \geq 0 \tag{LL}$$

$$p_{10}\bar{w}^A + (1 - p_{10})\underline{w}^A - \psi \geq p_{00}\bar{w}^A + (1 - p_{00})\underline{w}^A \tag{3.25}$$

$$p_{10}\bar{w}^B + (1 - p_{10})\underline{w}^B \geq p_{11}\bar{w}^B + (1 - p_{11})\underline{w}^B - \theta \tag{3.26}$$

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A - \rho \geq p_{10}\bar{w}^A + (1 - p_{10})\underline{w}^A - \psi \tag{3.27}$$

$$p_{01}\bar{w}^B + (1 - p_{01})\underline{w}^B - \alpha\theta - \rho \geq p_{10}\bar{w}^B + (1 - p_{10})\underline{w}^B \tag{3.28}$$

and (3.29), (3.30).

The agents' second-period incentive constraints given $T = 1$ are the same as in part (i), (3.29) and (3.30). Second-period incentive constraints given $T = 0$, (3.25) and (3.26) ensure that it is agent A's best response to select a high effort given B's action, while it is B's best response to choose a low effort. First-period incentive constraints, (3.27) and (3.28), reflect that it is the agents' mutual best responses to choose a high task effort.

The participation constraints for both agents are not binding because they are implied by the respective first-period incentive constraints, (3.27) and (3.28) and limited liability constraints for $\underline{w}^i$. Therefore, the participation constraints are slack and the limited liability constraints for $\underline{w}^{i*} = 0 \; \forall i = A, B$ are binding to minimize the expected costs.

For agent A any wage that satisfies

$$\frac{\psi}{p_{11} - p_{01}} \geq \bar{w}^A \geq \frac{\psi}{p_{10} - p_{00}}, \frac{\rho - \psi}{p_{01} - p_{10}} \geq 0$$

fulfills all three constraints for a different set of parameters. The first-period incentive constraint, (3.27), is binding if

$$\frac{\rho - \psi}{p_{01} - p_{10}} \geq 0 \;\text{ and }\; \frac{\psi}{p_{11} - p_{01}} \geq \frac{\rho - \psi}{p_{01} - p_{10}} \geq \frac{\psi}{p_{10} - p_{00}}.$$

The second-period incentive constraint, (3.25), is binding if

$$\frac{\psi}{p_{10} - p_{00}} \geq \frac{\rho - \psi}{p_{01} - p_{10}} \quad \text{and} \quad \frac{\psi}{p_{11} - p_{01}} \geq \frac{\psi}{p_{10} - p_{00}}.$$

Last but not least, the second-period incentive constraint, (3.29), binds if

$$\frac{\psi}{p_{11} - p_{01}} \geq \frac{\psi}{p_{10} - p_{00}}, \frac{\rho - \psi}{p_{01} - p_{10}}.$$

Agent B's first-period incentive constraint implies the second-period incentive constraint (3.30). The right-hand sides of both constraints are equivalent, while the left-hand side of (3.28) is strictly smaller. Thus, (3.30) is slack. Any wage that satisfies

$$\frac{\theta}{p_{11} - p_{10}} \geq \bar{w}^B \geq \frac{\alpha\theta + \rho}{p_{01} - p_{10}} \geq 0$$

satisfies all necessary constraints. Agent B's first-period incentive constraint is binding as it represents the lowest possible wage that satisfies all constraints for $\theta \, \frac{p_{01}-p_{10}}{p_{11}-p_{10}} \geq \alpha\theta + \rho$. Notice that the optimal wage must also ensure that the limited liability constraints are fulfilled. Therefore, it must be that $p_{01} > p_{10}$.

The wages that implement effort profiles $(0,1)$ for $T = 1$ and $(1,0)$ for $T = 0$ are given by

$$\bar{w}^A = \begin{cases} \frac{\psi}{p_{11}-p_{01}} & \text{if } \; \psi \, \frac{p_{11}-p_{10}}{p_{11}-p_{01}} \geq \rho \;\&\; p_{10} + p_{01} \geq p_{11} + p_{00} \\ \frac{\psi}{p_{10}-p_{00}} & \text{if } \; \psi \, \frac{p_{01}-p_{00}}{p_{10}-p_{00}} \geq \rho \;\&\; p_{10} + p_{01} \geq p_{11} + p_{00} \\ \frac{\rho-\psi}{p_{01}-p_{10}} & \text{if } \; \psi \, \frac{p_{11}-p_{10}}{p_{11}-p_{01}} \geq \rho \geq \psi \, \frac{p_{01}-p_{00}}{p_{10}-p_{00}}, \end{cases}$$

$$\underline{w}^A = 0 \quad \textit{and}$$

$$\bar{w}^B = \frac{\alpha(1)\theta + \rho}{p_{01} - p_{10}} \quad \text{for} \quad \theta \, \frac{p_{01} - p_{10}}{p_{11} - p_{10}} \geq \alpha(1)\theta + \rho,$$

$$\underline{w}^B = 0.$$

Notice that the contract can only satisfy the limited liability conditions for $p_{01} \geq p_{10}$.[71] Otherwise, agent B's wage is negative. For small ρ, the principal still bases A's rent on their task effort cost, ψ. Thus, compensating the agent for a high transfer effort but not paying them enough so that they would also choose a high task effort given $T = 1$. For intermediate values of ρ, notice that A's wage only meets the limited liability conditions if $p_{10} \geq p_{01}$ and $\psi \geq \rho$ or if $p_{01} \geq p_{10}$ and $\rho \geq \psi$. Taking into account that for B's wage to conform to the limited liability conditions it must be that $p_{01} \geq p_{10}$, ρ should be larger or equal to ψ to satisfy the limited liability conditions for agent A. The principal pays A a rent that is based on the difference between the transfer costs and the task effort costs, such that they are induced to only choose a high transfer effort. Agent B's wage is non-negative if $p_{01} \geq p_{10}$. The principal compensate B for a high transfer and task effort by basing the rent on the sum of the effort costs. This rent induces B to only choose a high task effort given $T = 1$ if the effort costs without a transfer are larger than the effort costs with a transfer such that there is a gain in productivity.

The optimization problem for effort profiles $(0, 1)$ for $T = 1$ and $(0, 0)$ for $T = 0$ is given by

$$\min_{w^A, w^B} p_{01}(\bar{w}^A + \bar{w}^B) + (1 - p_{01})(\underline{w}^A + \underline{w}^B)$$

subject to

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A - \rho \geq 0 \qquad (PC^A)$$

$$p_{01}\bar{w}^B + (1 - p_{01})\underline{w}^B - \alpha(1)\theta - \rho \geq 0 \qquad (PC^B)$$

$$\bar{w}^A, \underline{w}^A, \bar{w}^B, \underline{w}^B \geq 0 \qquad \text{(LL)}$$

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A \geq p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi \qquad (3.29)$$

$$p_{01}\bar{w}^B + (1 - p_{01})\underline{w}^B - \alpha(1)\theta \geq p_{00}\bar{w}^B + (1 - p_{00})\underline{w}^B \qquad (3.30)$$

$$p_{00}\bar{w}^A + (1 - p_{00})\underline{w}^A \geq p_{10}\bar{w}^A + (1 - p_{10})\underline{w}^A - \psi \qquad (3.31)$$

$$p_{00}\bar{w}^B + (1 - p_{00})\underline{w}^B \geq p_{01}\bar{w}^B + (1 - p_{01})\underline{w}^B - \theta \qquad (3.32)$$

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A - \rho \geq p_{00}\bar{w}^A + (1 - p_{00})\underline{w}^A \qquad (3.33)$$

[71] One possible explanation is that agent B's task is more relevant for the performance of the team than agent A's task.

$$p_{01}\bar{w}^B + (1-p_{01})\underline{w}^B - \alpha(1)\theta - \rho \geq p_{00}\bar{w}^B + (1-p_{00})\underline{w}^B \tag{3.34}$$

Second-period incentive constraints, (3.29) and (3.30), ensure that given $T = 1$ it is agent A's (B's) best response to choose a low (high) effort. Second-period incentive constraints, (3.31) and (3.32), ensure that given $T = 0$ it is the agents mutual best response to choose a low effort. First-period incentive constraints (3.33) and (3.34) reflect that it is both agents' mutual best response to choose a high transfer effort.

The participation constraints for both agents are not binding because they are implied by the respective first-period incentive constraints, (3.33) and (3.34) and the limited liability constraints for $\underline{w}^i$. Therefore, the participation constraints are slack and limited liability constraints for $\underline{w}^{i*} = 0 \ \forall i = A, B$ is binding.

For agent A any wage that satisfies

$$\frac{\psi}{p_{11}-p_{01}}, \ \frac{\psi}{p_{10}-p_{00}} \geq \bar{w}^A \geq \frac{\rho}{p_{01}-p_{00}}$$

can satisfy all three incentive constraints. The first-period incentive constraint represents the lowest possible wage that can also fulfill the second-period incentive constraints under certain parameter restrictions. When these parameter restrictions do not hold, one of the second-period incentive constraints is binding. That is, the first-period incentive constraint is binding if

$$\frac{\psi}{p_{11}-p_{01}}, \ \frac{\psi}{p_{10}-p_{00}} \geq \frac{\rho}{p_{01}-p_{00}}.$$

Second-period incentive constraint (3.29) is binding if

$$\frac{\psi}{p_{11}-p_{01}} \geq \frac{\rho}{p_{01}-p_{00}} \quad \text{and} \quad \frac{\psi}{p_{10}-p_{00}} \geq \frac{\psi}{p_{11}-p_{01}}.$$

Second-period incentive constraint (3.31), is binding if

$$\frac{\psi}{p_{10}-p_{00}} \geq \frac{\rho}{p_{01}-p_{00}} \quad \text{and} \quad \frac{\psi}{p_{11}-p_{01}} \geq \frac{\psi}{p_{10}-p_{00}}.$$

Agent B's first-period incentive constraint, (3.34), implies the second-period incentive constraint (3.30), because while the right-hand sides are equivalent, the left-hand side of the first-period incentive constraint is strictly smaller due to $\rho > 0$. Thus, (3.30) is slack.

Any wage that satisfies

$$\frac{\theta}{p_{01}-p_{00}} \geq \bar{w}^B \geq \frac{\alpha(1)\theta + \rho}{p_{01}-p_{00}}$$

fulfills all necessary incentive constraints. Thus, the sufficient constraints, (3.32) and (3.34) are satisfied for the same parameter constellation. However, (3.34) gives the lower wage of the two and therefore it is binding. Agent B's second-period incentive constraint given $T = 0$ is an upper bound for $\bar{w}^B$, such that $\theta \geq \alpha(1)\theta + \rho$ is a necessary condition for B's wage scheme.

The wages that implement effort profiles $(0,1)$ for $T = 1$ and $(0,0)$ for $T = 0$ are given by

$$\bar{w}^A = \begin{cases} \frac{\rho}{p_{01}-p_{00}} & \text{if } \psi\,\frac{p_{01}-p_{00}}{p_{10}-p_{00}},\ \psi\,\frac{p_{01}-p_{00}}{p_{11}-p_{01}} \geq \rho \\ \frac{\psi}{p_{10}-p_{00}} & \text{if } \psi\,\frac{p_{01}-p_{00}}{p_{10}-p_{00}} \geq \rho \geq \psi\,\frac{p_{01}-p_{00}}{p_{11}-p_{01}} \ \&\ p_{01}+p_{10} \geq p_{11}+p_{00} \\ \frac{\psi}{p_{11}-p_{01}} & \text{if } \psi\,\frac{p_{01}-p_{00}}{p_{11}-p_{01}} \geq \rho \geq \psi\,\frac{p_{01}-p_{00}}{p_{10}-p_{00}} \ \&\ p_{11}+p_{00} \geq p_{10}+p_{01}, \end{cases}$$

$$\underline{w}^A = 0 \quad \textit{and}$$

$$\bar{w}^B = \frac{\alpha(1)\theta + \rho}{p_{01} - p_{00}} \quad \text{for} \quad \theta \geq \alpha(1)\theta + \rho, \qquad \underline{w}^B = 0.$$

Agent A must be compensated for their transfer costs ρ but must not be induced to choose a high task effort. Therefore, the principal pays them a rent that is based on ψ, their task effort costs, if ρ takes on larger values. However, if ρ is small it suffices to base their rent on ρ itself. Agent B's wage $\bar{w}^B$ is determined by their first-period incentive constraint. The principal pays them a rent based on the sum of effort costs if this sum is smaller than θ, the task effort costs, given $T = 0$. This ensures that B only chooses a high task effort after a transfer occurred.

I show that there are no other contracts that induce a transfer except for the ones in Proposition 3.3 through a proof by contradiction. Suppose towards a contradiction that a contract exist that induces a knowledge transfer and implements effort profiles $(1,1)$ for $T = 1$ and $(1,1)$ or $(0,1)$ for $T = 0$. First, take as given that the principal induces $(1,1)$ for $T = 0$. Agent A's first-period incentive constraint is given by

$$p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi - \rho \geq p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi,$$

which reveals that because ρ is positive, agent A does not have an incentive to exert a transfer effort. Thus, this does not lead to a Nash equilibrium with a transfer. Second, given the principal implements effort profile $(0,1)$ for $T = 0$, agent A's incentive constraints are given by

$$p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi - \rho \geq p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A,$$

$$p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi \geq p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A,$$

$$p_{01}\bar{w}^A + (1 - p_{01})\underline{w}^A \geq p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi.$$

To satisfy both second-period incentive constraints simultaneously they need to hold with equality such that $\Delta w^A = \frac{\psi}{p_{11}-p_{01}}$. However, with this wage difference the first-period incentive constraint cannot be satisfied since it implies that $\Delta w^A \geq \frac{\psi+\rho}{p_{11}-p_{01}}$

and ρ is positive. Therefore, a Nash equilibrium with a transfer cannot be reached by implementing effort profile $(1,1)$ for $T=1$ and effort profile $(1,1)$ or $(0,1)$ for $T=0$.

Assume towards a contradiction that a contract exists that induces a transfer and implements effort profile $(0,1)$ for $T=1$ and $(0,1)$ or $(1,1)$ for $T=0$. First, given the principal implements $(0,1)$ for $T=0$, agent A's first-period incentive constraint is given by

$$p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A - \rho \geq p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A.$$

This incentive constraint cannot be satisfied since $\rho > 0$.Thus, there is no contract for agent A such that they exert a transfer effort. Second, given the principal induces effort profile $(1,1)$ for $T=0$, agent A's incentive constraints are

$$p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A \geq p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi,$$

$$p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi \geq p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A,$$

$$p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A - \rho \geq p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi.$$

To satisfy both second-period incentive constraints simultaneously, they have to hold with equality, such that $\Delta w^A = \frac{\psi}{p_{11}-p_{01}}$. However, this wage difference cannot meet the first period incentive constraint, which requires that $\Delta w^A \leq \frac{\psi-\rho}{p_{11}-p_{01}}$. Therefore, there exists no Nash equilibrium with a transfer, where the principal implements effort profile $(0,1)$ for $T=1$ and effort profile $(0,1)$ or $(1,1)$ for $T=1$.

Assuming towards a contradiction that there exists a contract that induces a transfer and implements effort profile $(1,0)$ for $T=1$, I check the different effort profiles the principal can implement for $T=0$ starting with $(1,0)$. The agents' first-period incentive constraints,

$$p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \rho - \psi \geq p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi,$$

$$p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B - \rho \geq p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B,$$

cannot be satisfied since $\rho > 0$. Thus, neither agent exerts a task effort and a transfer cannot take place. Given the principal induces $(1,1)$ for $T=0$, the agent A's first-period incentive constraint cannot be satisfied because $\rho > 0$ and $p_{11} > p_{10}$,

$$p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi - \rho \geq p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi,$$

such that A does not have an incentive to exert a transfer effort. To satisfy agent B's second-period incentive constraints,

$$p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B \geq p_{11}\bar{w}^B + (1-p_{11})\underline{w}^B - \theta,$$

$$p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B \leq p_{11}\bar{w}^B + (1-p_{11})\underline{w}^B - \theta,$$

they have to hold with equality, such that $\Delta w^B = \frac{\theta}{p_{11}-p_{10}}$. However, with this wage difference the first-period incentive constraint,

$$p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B - \rho \geq p_{11}\bar{w}^B + (1-p_{11})\underline{w}^B - \theta,$$

does not hold. Given the principal implements $(0,0)$ for $T=0$ agent A's incentive constraints are given by

$$p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi - \rho \geq p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A,$$

$$p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi \geq p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A,$$

$$p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A \geq p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi.$$

The second-period incentive constraints can only be satisfied simultaneously for $\Delta w^A = \frac{\psi}{p_{10}-p_{00}}$. However, this wage does not satisfy the first-period incentive constraint according to which $\Delta w^A \geq \frac{\psi+\rho}{p_{10}-p_{00}}$. Finally, given the principal induces effort profile $(0,1)$ for $T=0$, agent A's incentive constraints are given by

$$p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi - \rho \geq p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A \quad \Leftrightarrow \Delta w^A \geq \frac{\psi+\rho}{p_{10}-p_{01}},$$

$$p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi \geq p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A \quad \Leftrightarrow \Delta w^A \geq \frac{\psi}{p_{10}-p_{00}},$$

$$p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A \geq p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi \quad \Leftrightarrow \Delta w^A \leq \frac{\psi}{p_{11}-p_{01}}.$$

In order for the first-period incentive constraint to be satisfied it must be that $p_{10} \geq p_{01}$. Otherwise, the left-hand side is smaller than the right-hand side and the first-period incentive cannot be fulfilled. Given $p_{10} \geq p_{01}$ the first-period incentive constraint implies the second incentive constraint since $p_{01} > p_{00}$ such that this constraint is never binding. The last incentive constraint is fulfilled if

$$\frac{\psi}{p_{11}-p_{01}} \geq \frac{\psi+\rho}{p_{10}-p_{01}}.$$

However, this restriction cannot be satisfied because $p_{11} > p_{10}$ and $\rho > 0$. Thus, implementing effort profile $(1,0)$ for $T=1$ does not result in a Nash equilibrium with a transfer.

Next, we assume towards a contradiction that there exists a contract that induces a transfer and implements effort profile $(0,0)$ for $T=1$. I go through the different effort profiles the principal can implement for $T=0$, beginning with $(0,0)$. Again, the agents' first-period incentive constraints,

$$p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A - \rho \geq p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A,$$

$$p_{00}\bar{w}^B + (1-p_{00})\underline{w}^B - \rho \geq p_{00}\bar{w}^B + (1-p_{00})\underline{w}^B$$

reveal that agents cannot be induced to choose a high transfer effort since $\rho > 0$. Therefore, this does not lead to a Nash equilibrium where a transfer takes place. Given the principal induces $(1,1)$ for $T = 0$, agent A's incentive constraints are

$$p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A - \rho \geq p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi,$$

$$p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A \geq p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi,$$

$$p_{11}\bar{w}^A + (1-p_{11})\underline{w}^A - \psi \geq p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A.$$

However, first and last constraint contradict each other because $p_{01} > p_{00}$ and $\rho > 0$. The same applies for agent B with $p_{10} > p_{00}$. Thus, this also does not support a contract that leads to a transfer. Given the principal implements $(1,0)$ for $T = 0$, agent A's incentive constraints,

$$p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A - \rho \geq p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi,$$

$$p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A \geq p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi,$$

$$p_{10}\bar{w}^A + (1-p_{10})\underline{w}^A - \psi \geq p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A,$$

reveal that the first and the last incentive constraint cannot be satisfied at the same time. Whereas, for agent B the first-period incentive constraint cannot be fulfilled,

$$p_{00}\bar{w}^B + (1-p_{00})\underline{w}^B - \rho \geq p_{10}\bar{w}^B + (1-p_{10})\underline{w}^B$$

since $p_{10} > p_{00}$ and $\rho > 0$. Finally, given the principal induces $(0,1)$ for $T = 0$, agent A's first-period incentive constraint can never be satisfied,

$$p_{00}\bar{w}^A + (1-p_{00})\underline{w}^A - \rho \geq p_{01}\bar{w}^A + (1-p_{01})\underline{w}^A,$$

since $p_{01} > p_{00}$ and $\rho > 0$. Agent B's incentive constraints are

$$p_{00}\bar{w}^B + (1-p_{00})\underline{w}^B - \rho \geq p_{01}\bar{w}^B + (1-p_{01})\underline{w}^B - \theta$$

$$p_{00}\bar{w}^B + (1-p_{00})\underline{w}^B \geq p_{01}\bar{w}^A + (1-p_{01})\underline{w}^B - \theta$$

$$p_{01}\bar{w}^B + (1-p_{01})\underline{w}^B - \theta \geq p_{00}\bar{w}^B + (1-p_{00})\underline{w}^B.$$

However, the first and the last incentive constraint cannot be satisfied simultaneously. Hence, implementing effort profile $(0,0)$ for $T = 1$ does not result in a Nash equilibrium where a transfer takes place.

Therefore, except for the contracts characterized in Proposition 3.3 the principal cannot induce a transfer in equilibrium with any other effort profiles.

Proof of Proposition 3.4

Suppose that $p_{11} > 0$ and $p_{10}, p_{01}, p_{00} = 0$, the principal induces a transfer and implements effort profile $(1,1)$ for $T = 1$ and effort profile $(0,0)$ for $T = 0$. The optimization problem is

$$\min_{w^A, w^B \geq 0} p_{11}(\bar{w}^A + \bar{w}^B) + (1 - p_{11})(\underline{w}^A + \underline{w}^B)$$

subject to

$$\underline{w}^A, \underline{w}^B, \bar{w}^A, \bar{w}^B \geq 0 \tag{LL}$$

$$p_{11}\bar{w}^A + (1 - p_{11})\underline{w}^A - \psi - \rho \geq 0 \tag{PC^A}$$

$$p_{11}\bar{w}^B + (1 - p_{11})\underline{w}^B - \alpha(1)\theta - \rho \geq 0 \tag{PC^B}$$

$$p_{11}(\bar{w}^A - \underline{w}^A) - \psi \geq 0 \tag{3.35}$$

$$p_{11}(\bar{w}^B - \underline{w}^B) - \alpha(1)\theta \geq 0 \tag{3.36}$$

$$0 \geq -\psi \tag{3.37}$$

$$0 \geq -\theta \tag{3.38}$$

$$p_{11}(\bar{w}^A - \underline{w}^A) - \psi - \rho \geq 0 \tag{3.39}$$

$$p_{11}(\bar{w}^B - \underline{w}^B) - \alpha(1)\theta - \rho \geq 0 \tag{3.40}$$

Due to limited liability constraints the principal cannot use a negative wage and therefore minimizes the expected costs with binding limited liability constraints for $\underline{w}^i$. Thus, first-period incentive constraints or alternatively the participation constraints for agents A and B are binding and yield the optimal wages. The second-period incentive constraints, (3.37) and (3.38), ensure that it is each agent's best response to not exert an effort for $T = 0$ and are always satisfied, since $\psi,\ \theta > 0$.

To show that this contract is unique and therefore optimal, take a look at the incentive constraints in the proof of Proposition 3.3. Plugging in $p_{01},\ p_{10},\ p_{00} = 0$ reveals that there is always at least one incentive constraint that cannot be satisfied. All these situations have in common that the principal implements an effort profile where one agent exerts an effort alone. However, under the given assumption the success probability is zero even if one agent exerts an effort. Therefore, the agents pay the effort costs but get no higher success probability in return. The principal cannot induce an agent to do so, so that implementing effort profile $(1,1)$ for $T=1$ and $(0,0)$ for $T=0$ is a unique Nash equilibrium.

Suppose that $p_{11} > p_{10} \gtreqless p_{01} > p_{00} = 0$, as above the principal induces the same behavior and implements the same effort profiles. The objective function, limited liability conditions, participation constraints and first-period incentive constraints, (3.39) and (3.40), remain the same. However, the second-period incentive constraints change:

$$(p_{11} - p_{01})(\bar{w}^A - \underline{w}^A) - \psi \geq 0 \tag{3.41}$$

$$(p_{11} - p_{10})(\bar{w}^B - \underline{w}^B) - \alpha(1)\theta \geq 0 \tag{3.42}$$

$$\psi \geq p_{10}(\bar{w}^A - \underline{w}^A) \tag{3.43}$$

$$\theta \geq p_{01}(\bar{w}^B - \underline{w}^B). \tag{3.44}$$

As before, the limited liability constraints for $\underline{w}^i$ are binding such that the first-period incentive constraints and participation constraints are equal. The first-period incentive constraints imply the second-period incentive constraints (3.41) and (3.42) for agents A and B, respectively. The first-period incentive constraints are binding for

$$\frac{p_{11} - p_{10}}{p_{10}}\,\psi \geq \rho \qquad \frac{p_{11}}{p_{01}}\,\theta \geq \alpha(1)\theta + \rho.$$

When the first-period incentive constraints are binding, the first-best outcome is reached and the wages are therefore,

$$w^A = \left(\frac{\psi + \rho}{p_{11}}, 0\right) \qquad \text{and} \qquad w^B = \left(\frac{\alpha(1)\theta + \rho}{p_{11}}, 0\right).$$

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Erklärung zu Selbstständigkeit und Hilfsmitteln

Hiermit erkäre ich, dass ich die Dissertation selbständig und nur unter der Verwendung der angegebenen Hilfen und Hilfsmittel angefertigt habe. Software:

- Stata
- Mathematica
- MiKTex

Literature: siehe Literatureverzeichnis

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Berlin, den 28. Februar 2022

Friederike Julia Heiny