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This dissertation was completed when I worked at the Düsseldorf Institute for Competition Economics (DICE) at Heinrich-Heine-Universität as a doctoral researcher. However, I joined the DICE already in 2011 as a student assistant. I thank Michael Coenen for giving me this opportunity which granted me insights into economic research very early on. My research has benefited greatly from discussions with professors and colleagues who became friends.

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Introduction

In the last two decades no other technology has shaped the way people interact and firms compete more than the internet. Its use and availability skyrocketed dramatically: In 1992 global internet traffic amounted to only 100 Gigabyte (GB) per day. In 2017 it already amassed to 46,600 GB per second and is expected to triple again by 2022 according to Cisco (2019). The number of internet users is annually growing at a 7% rate and thus faster than the worldwide population growth of 1%. Hence, internet access becomes increasingly available for people across all continents (Cisco, 2019).

This development offers a variety of industries new possibilities to decrease costs, offer new products or even develop new business models. This in turn poses multiple challenges for governments and public authorities. These encompass providing a potent network infrastructure which is capable of satisfying present and future data demands. Further, counteracting economic inefficiencies that may arise from new products or business models. And, lastly, ensuring that all stakeholders, especially consumers, benefit from the advancement of new services and will not be subject to anticompetitive behavior that might be borne by the dynamics of new digital markets. It is the aim of this thesis to evaluate the competition on digital markets and derive policy relevant insights to face those challenges.

Before a "digital" market or even a "digital" service can exist, there must be a transmission of information in the form of 0 and 1 first. This signal is originally transmitted via a wire that connects the sender and the receiver. Since every user nowadays is sender and receiver alike, multilateral connection is realized by access to a communication network. Through such networks users are able to access the internet and with that communicate, shop online, stream content or control the heating of one's flat. On the other side, firms are able to reach their customers, advertise on their platforms or offer innovative services. Some of those future products, among others, will be autonomously driving cars, Internet of Things applications or e-Medicine. While the transmission speed of today's networks might be sufficient for current demands it will not sustain in the future.

In order to change that, the often copper based legacy infrastructure has to be upgraded to a fiber-optic structure. This however is costly. In a time in which network operators' revenues from traditional business models stagnate (ETNO, 2019) and competition from content providers becomes more fierce (European Parliament, 2015), this upgrading process advances much slower in many countries than desired by policy makers.

Chapter 1 entitled **"Fiber vs. Vectoring: Limiting Technology Choices in Broadband Expansion"** therefore examines structural drivers of fiber deployment and the effectiveness of policy interventions such as subsidies and a technologically selective regulation. To do so, the extensive and intensive margin of first time investment into fiber deployment are empirically analyzed based on the micro level of German municipalities. Both competing infrastructure architectures of Vectoring and TV-Cable as well as the deployment effect of subsidies are considered. A natural experiment in the German telecommunications market from August 2013 to July 2017 is exploited to evaluate a technologically restrictive deployment regulation, which was implicitly mandated by the European Commission (2016). During this period the competing infrastructure type of Vectoring was not available in certain network areas such that fiber and TV-Cable were the only available alternatives to provide high-speed internet access.

The analysis finds that a municipality is more likely to be accessed with fiber if it is large, has a younger population and is closely located to an already accessed municipality. While technology competition through Vectoring is beneficial for the likelihood of first time investment, it is detrimental for the intensive margin as it lowers the increase in fiber coverage, that is, the fraction of households served. However, the data does not provide a significant effect of a technologically restrictive deployment environment but suggests that subsidies are highly effective. An additional funding of 100,000€ corresponds to a 3 to 4 percentage point higher likelihood of fiber deployment. Therefore, the findings of Chapter 1 not only encourage policy makers to subsidize areas where fiber deployment is desired but also identify structural and technological drivers which indicate where fiber deployment is more likely to arise naturally by market forces and in which municipalities it might crucially depend on funding.

Digital products and services often allow providers to gather customer data. This can be the geographical tracking of a user's mobile device, an online shopping history or just a collection of recent search queries. Firms analyze these data to learn about their users' motion profiles or preferences and adapt their products accordingly. For instance, a network operator learns at which times of the day and in which areas congestion arises and can improve network capacity accordingly. A streaming platform infers from search queries which currently not offered content would be a desired addition to its existing portfolio. Or a dominant search engine is able to design whole new products based on consumers' general searches.

The possibility to customize products and strategically choose deployment extent, variety and other product components provides a second dimension, apart from the price, which is of relevance for the competition on digital markets. While inefficiencies in the price dimension are generally well understood in economics, inefficiencies with respect to customization, that is, the horizontal differentiation of products are not.

Chapter 2 entitled **"Monopoly Customization with Log-concave Consumer Preferences"** theoretically examines a monopolist's two dimensional optimization problem with respect to an access price and chosen customization degree of the product offered. In the spatial model of horizontal differentiation based on the works of Hotelling (1929) consumer preferences are reflected by a general log-concave density function. This class of distributions allows for non-uniform preferences which can be assumed to better fit reality. In this setting, the monopolist chooses the product in form of an interval which represents the degree of customization and perfectly matches a variety of preferences. The interpretation of this theoretical framework is manifold. It can be related to population density and the deployment extent of a communication network, to the distribution of tastes and the portfolio of a streaming platform, or to a non-digital context, for instance, time preferences to do purchases and the actual opening hours of shops.

First, the monopoly equilibrium is characterized and conditions under which the monopolist's product customization is socially inefficient are derived. Employing a specific symmetric, non-uniform density function illustrates how the inefficiency of providing a too narrow interval of product characteristics relates to the shape of the consumers preference distribution. The analysis finds that for more (less) concentrated preferences, this inefficiency tends to be large (small) for narrow interval products and small (large) for wide ones. Translated to the setting of streaming content implies that a monopolistic supplier would cater the portfolio too strongly to "mainstream" tastes while niche genres would be underrepresented. If one considers the deployment of network infrastructure, a monopolist would concentrate too much on the densely populated areas while neglecting the outskirts of settlements if the concentration gradient is large. This finding could is of policy relevance especially when network deployment is lacking behind expectations in areas that exhibit a large variation in population densities.

The ability to customize products or the complexity of digital services in general often gives rise to consumer switching costs. In this case, buying a product of another supplier involves additional, often non-monetary costs apart from the purchasing price. For instance, a software user who is accustomed to working with applications from one supplier, has to take into account an additional familiarization period when considering a switch to a product of a competing supplier. This familiarization is the switching cost and leads to consumers tending to re-buy products from their original suppliers. While the switching costs in the previous example arise somewhat naturally, they are often attached strategically to certain products and services - especially on digital markets. Social networks, streaming platforms and other services that work with user created content try to hinder users from taking their content data with them when switching suppliers. These practices are motivated by increasing customer retention and exploiting own customers' reduced price sensitivity.

However, in theory, the prospect of reduced competition for existing customers is paralleled by an increased competitive pressure for consumers who enter the market for the first time and have not bought a product yet. Firms try to attract those consumers with rebates or introductory offers in order to establish an installed base. Consider, for instance, reduced software licenses that are distributed at a discounted price to students or other groups. Once the status as a student voids, a consumer has to buy a license for the full version at the regular price if she wants to continue to use the software. These reversed pricing incentives, that is, low prices to new consumers and higher prices to existing customers, are often referred to as "invest and harvest" behavior. The aggregate effect on prices, the competitiveness of markets and thus the incentives to collude are considered unclear.

Chapter 3 entitled **"Let's Lock Them in: Collusion under Consumer Switching Costs"** aims at filling this research gap. In a laboratory experiment subjects take the role of firms and choose selling prices towards new consumers and those who already bought a product. While the competitive setting is based on Klemperer (1995, Section 3.2), the presence of switching costs and the firms' ability to communicate is varied. With this 2x2 factorial treatment design, the experiment is able to identify switching costs' effect in both an environment of explicit collusion and without, as well as the gains from explicit communication either with our without switching costs.

In the case of absent communication switching costs are found to reduce prices towards consumers who have not bought yet, while the price level towards existing customers is not affected. Hence, the "investment" motive outweighs the "harvesting". Further, communication facilitates the coordination on higher prices and helps to overcome the "investment" pressure. This is in line with findings of Fonseca and Normann (2012) and Cooper and Kühn (2014) and thus shows that explicit agreements are generally attractive. Third, the degree of tacit collusion is less pronounced if consumers face switching costs, which comes with a downside though. It consequences monetary gains through communication to be distinctively higher and thus make explicit collusion the more lucrative which forms the fourth main result. Hence, switching cost markets may bear an increased risk for consumers to be subject to such anticompetitive behavior.

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Chapter 1

Fiber vs. Vectoring: Limiting Technology Choices in Broadband Expansion[♠]

Summary of the chapter

Developing an efficient upgrade path of legacy telecommunications infrastructure to a fiber-optics network is challenging. Network operators' profitability concerns, political agendas and structural conditions often stand in conflict. Using German micro-level data, we identify the structural determinants for fiber optics deployment and its extent. We also measure the role of technology competition from the existing infrastructures, VDSL-Vectoring and TV-Cable. By exploiting a natural experiment, a technologically restrictive policy as proposed by the European Commission is found to be ineffective in promoting fiber deployment. Policy interventions in the form of subsidies targeted at specific local infrastructure projects, however, raise the likelihood of fiber deployment by a substantial margin. A targeted, proactive policy approach is therefore needed to overcome structural and geographical disadvantages.

[♠]This chapter is co-authored with Alex Korff.

1.1 Introduction

Communication networks are not only the backbone of today's digital era economy but also shape social interactions and with that our society. Investment in those networks therefore exerts positive effects on employment, growth, innovation and other economic indicators. This is achieved by reducing costs of existing business models while simultaneously paving the way for services and applications which rely on more potent networks and transmission rates. For the near future, these requirements are embodied by emerging services such as the Internet of Things, real-time traffic solutions and e-Medicine whose data demands are already foreshadowed today by streaming and cloud services. For this reason, investing in existing communication networks is paramount to cope with the exponential growth of data consumption and provide a hotbed for future innovations.[1] In technical terms, this means upgrading legacy networks, often based on copper, to a state-of-the-art and future-proof fiber-optics based architecture.

Apart from fiber wires, a consumer's access to a fixed line communication network can be realized by means of copper wires or TV-Cable. While all of these access technologies rely on fiber to some degree, only Fiber-to-the-premise (FttP) directly connects a household with fiber optics.[2] Other hybrid technologies like VDSL2-Vectoring (Vectoring) also employ legacy copper double-wires on the local loop ("last mile") or rely on the hybrid-fiber-coaxial (HFC/TV-Cable) technology. Such technologies are readily available and less costly to roll out compared to FttP. This, naturally, affects network operators' deployment decisions and is especially relevant in remote areas where installing fiber to every household might not be efficient.

In an effort to influence operators and accelerate the upgrading process of fixed line networks, the European Commission (EC) formulated a broadband target in 2016 envisioning the coverage of all European households with downlink speeds of at least 100 Mbit/s by 2025. Additionally, this bandwidth has to be provided by an infrastructure which can be technically leveraged to provide Gigabit speed in the near future (see European Commission, 2016a).[3] This Gigabit amendment effectively rules out Vectoring as a viable alternative from the available technologies. The EC (2016b, p. 19) is concerned that "strategic profit-maximizing considerations at the operator level would delay the transition" to FttP structures. However, the assumption underlying this argument, namely that an incumbent's copper-based Vectoring deployment will act as a substitute to any FttP investment, has not been examined by scientific research so far.

[1] Cisco (2017) estimates the data traffic over fixed-line connections to increase exponentially from 65,94 Petabyte(PB)/month from 2016 up to 187,39 PB/month by 2021. Note that 1 Petabyte(PB) = 1,000 Terabyte(TB) = 1,000,000 Gigabyte(GB).

[2] FttP is a shorthand for Fiber-to-the-Home/Building (FttH/B).

[3] Gigabit speed refers to download rates of more than 1 Gbit/s. Note that 1 Gigabit (Gbit) = 1000 Megabit (Mbit).

We aim to close this gap by investigating structural determinants of FttP deployment and effects resulting from infrastructure competition.

This study is the first, to the best of our knowledge, investigating FttP deployment as a supply side outcome at the micro-level. Using municipality-level data from Germany, we examine the influence of structural determinants of FttP deployment at the extensive and intensive margin. We also account for technology competition from the two competing architectures existing in Germany, that is, Vectoring and HFC.

We complement this part of the study with an analysis of policy interventions such as technology regulation and deployment subsidies. We exploit a natural experiment in the German telecommunications market from December 2013 to June 2017 to examine effects of a technologically restrictive deployment regulation, a situation deemed favorable by the EC. Due to exogenous, technological restrictions in the legacy access network, Vectoring was inoperable and banned in certain areas around network nodes, while households in all other areas could be accessed. This provides treatment areas within German municipalities in which higher bandwidths could only be achieved by FttP or HFC structures and control areas in which all technologies were applicable. For the deployment effect of locally targeted subsidies, we use the subset of the federal state of Bavaria which operated a substantial subsidy program over the observation period.

We find the following main results: First, we observe a significant impact of structural characteristics on the extensive probability of deployment and its extent. Of these characteristics, market size and accessibility measures are most pronounced. Notably, an increase of a population's average age by one year in a municipality decreases the investment likelihood by one percentage point. Second, technology competition, especially from Vectoring, appears to increase the likelihood of FttP deployment. However, this positive effect coincides with a negative backlash at the intensive margin. Hence, Vectoring might signal deployment-worthy municipalities but simultaneously acts as a substitute once both networks coexist, it adversely affects the deployment extent. Third, a Vectoring restrictive regulation is ineffective and has neither an effect on the probability of FttP deployment, nor on deployment extent. Lastly, FttP-specific subsidies are demonstrated to be a highly effective policy tool. Every 100.000€ spent as part of the Bavarian subsidy program are associated with an increased likelihood of fiber deployment by 3 to 4 percentage points.

The remainder of the chapter is structured as follows. Section 1.2 provides literature findings on the main strands to which we contribute. Section 1.3 comments on Germany's infrastructure landscape and defines our identification. Section 1.4 elaborates on the data used in our analyses. Section 1.5 introduces the empirical strategy whose results are presented in Section 1.6. Finally, the chapter concludes in Section 1.7.

1.2 Literature

The vast literature on telecommunications networks establishes the view of the infrastructure as a general purpose technology in the sense of Bresnahan and Trajtenberg (1995). Communication networks are known to exert positive effects on a variety of macroeconomic indicators as well as individual firm or market performances (see Bertschek *et al.*, 2015). Given those positive effects, it is not surprising that the literature identifies different drivers and regulatory frameworks which best foster infrastructure deployment and investments.

We contribute to three different strands of the field. First, we complement the literature on structural drivers for investment in communications infrastructure by investigating these factors for a specific network type, FttP. Second, we examine regulatory approaches and their effect on infrastructure investment. While the effects of access obligations and state funding have been investigated, a technology restricting regulation has not yet been considered in this context. We close this gap. Lastly, we study the interaction of three competing network architectures - FttP, HFC and Vectoring - and their effect on FttP deployment from a supply-side perspective. Previous research has studied inter-technology competition only for the legacy infrastructures, DSL and HFC, and is focused on demand side indicators such as adoption and penetration.

In the first strand, regarding structural drivers, deployment is regularly explained by consumer demand for subsequent services or the costs of an infrastructure roll-out. Demand characteristics are household incomes and population ages, while the costs depend on the density of population and buildings, on topographic characteristics and institutional factors. These properties differ from the national down to the local level, as does actual investment. Cross-country and even regional (NUTS 2) or district-level (NUTS 3) analyses cannot properly capture these effects due to their aggregation. Not surprisingly, such studies either incorporate structural control variables but find no effects (Briglauer *et al.*, 2018, 2013) or abstain from using them (Grajek and Röller, 2012).[4] Empirical studies at the micro-level are scarce due to a lack of suitable data. Nardotto *et al.* (2015) study entry and broadband penetration on the local area level in the UK from 2005 to 2009. They determine significant effects of structural controls such as age, income and population density. Similarly, Bourreau *et al.* (2018) find a significance of population density and income for the number of active fiber operators in French municipalities over the period of 2010 to 2014.

The second strand concerns policy makers' options to influence providers' decisions where, and to which extent, to deploy broadband infrastructure in general and FttP in particular. In this regard, a regulation restricting technology choice is unprecedented

[4]Other cross-country approaches investigating effects on broadband penetration, a demand side measure rather than deployment, take the same approaches. Bouckaert *et al.* (2010) and Briglauer (2014) find structural controls to be insignificant, Distaso *et al.* (2006) do not incorporate them.

as an instrument to steer network deployment. Hence, this chapter is a first step in assessing the consequences of such a scheme. In contrast to this, the most common and most widely studied regulative tool is local loop unbundling (LLU) based on the "ladder of investment" hypothesis (Cave *et al.*, 2001; Cave and Vogelsang, 2003), which postulates a natural evolution from competition in services to competition in infrastructure. However, this hypothesis finds little support in the literature. Cambini and Jiang (2009) even observe that a systematic trade-off between LLU and investments in broadband infrastructure might exist instead. Cross-country empirical approaches by Grajek and Röller (2012) and Briglauer *et al.* (2018) support this interpretation, as do theoretical analyses highlighting distorted incentives to invest in fiber networks (Bourreau *et al.*, 2012; Inderst and Peitz, 2012). In conclusion, LLU may produce static efficiency of markets but fail to deliver dynamic efficiency and the transition towards infrastructure investment (Bacache *et al.*, 2014). On the other hand, more recent studies by Bourreau *et al.* (2018) and Calzada *et al.* (2018), relying on micro-level data similar to ours, do observe a positive effect of LLU on fiber deployment. Given these ambiguous effects of LLU on infrastructure deployment, Briglauer and Gugler (2013) argue that subsidies might be more effective in promoting fiber deployment. Briglauer (2019) himself provides support for this perspective by observing broadband coverage to increase by 18.4 to 25 percent if a municipality receives funding. This study is similar to ours in that it relies on Bavarian municipalities to investigate subsidy effects, although for a different time period and technology.

Lastly, the plethora of empirical studies on inter-technology competition mostly addresses the relationship between copper based (DSL) networks and TV-Cable (see Aron and Burnstein, 2003; Distaso *et al.*, 2006; Höffler, 2007; Bouckaert *et al.*, 2010; Nardotto *et al.*, 2015). These studies focus exclusively on demand side indicators such as broadband adoption or penetration as outcome variable of interest. They all conclude that inter-technology competition promotes the adoption and penetration of broadband. In contrast, studies investigating the effects of existing infrastructure on the deployment of new infrastructure are scarce. Briglauer *et al.* (2013) do investigate deployment of broadband infrastructure under the competition of cable networks in the EU27 for the period from 2005 to 2011. However, they subsume all kinds of Fttx structures from VDSL to FttH under the broadband tag. Their analysis does consequently not account for technology-specific quality differences which would be crucial in assessing multilateral competitive effects of the infrastructures. Our study is, therefore, a first step in understanding such interdependencies between three distinct competing infrastructures and the deployment of FttP.

1.3 Broadband infrastructure in Germany & identification

In this section, we compare the German network landscape to the regulatory demands placed upon it. As stated before, the EC postulates a broadband target of fixed line connections of 100 MBit/s for every household by the time of 2025 and a reasonable upgrade path to Gigabit connection for the chosen infrastructure (European Commission, 2016a). To this end, we review the fixed line technologies of FttP, HFC and Vectoring and comment on their ability to deliver the EC's conditions. Their deployment extent by December 2013 - the starting point of our observational period - is also summarized. Finally, we elaborate on our identification strategy for a technology-restrictive (Vectoring-free) regulation, which is based on the technological peculiarities of the German historic public switched telephone network (PSTN).

1.3.1 Infrastructure landscape

The first and most potent technology is fiber, specifically: *Fiber-to-the-premise (FttP)*. It subsumes deployments of fiber-optics reaching either the boundary of the end users' homes (FttH) or the respective residential building (FttB). For FttP, the entire "last mile", a shorthand for the wiring from the household's demarcation point to the main distribution frame (MDF), consists of fiber. This currently permits symmetric connections of over 10 Gbit/s in downlink and uplink, although the transmission itself is theoretically restricted only by the speed of light. Consequently, it is considered the most future proof network technology. On the other hand, deployment costs are substantial because existing copper double wires have to be replaced or overbuilt. Additionally, telecommunications infrastructure is traditionally installed underground in Germany, raising deployment costs further.

FttP has first been deployed in Germany in 2011 to the effect that only 2.78 percent of municipalities had been accessed by December 2013. The geographical deployment pattern is displayed in Panel A of Figure 1.1. These new networks are being operated by the incumbent - Deutsche Telekom - and other traditional internet providers (Vodafone, United Internet, Telefonica O2), but also by a large number of local carriers. The latter group includes municipality works, specifically founded local companies (M-net, Tele Columbus, NetCologne) and initiatives by municipal administration or citizens.

Hybrid-fiber-coaxial (HFC) networks, the second-most potent technology in Germany, uses fiber as well as coaxial wires of the legacy TV-Cable network (CATV). During our observational period from 12/2013 to 06/2017, two transmission standards

- DOCSIS 3.0 and 3.1 - were used simultaneously.[5] While the former was introduced in 2006 and offers a downlink of up to 1.5 Gbit/s and uplink of 200 Mbit/s, the latter was introduced in 2013 and permits a downlink of 10 Gbit/s and an uplink of 1 Gbit/s. Hence, HFC both satisfies the current broadband target and offers a reliable upgrade path to Gigabit as well.[6]

Deployment or expansion costs are moderate as most of the legacy CATV wiring is of continuous use and only the equipment installed in network nodes needs to be replaced. However, the network covers only approximately 70 percent of all German households and by December of 2013 only 27.77 percent of German municipalities had access to a high-speed HFC connection (see Panel B of Figure 1.1 for the geographical deployment pattern).

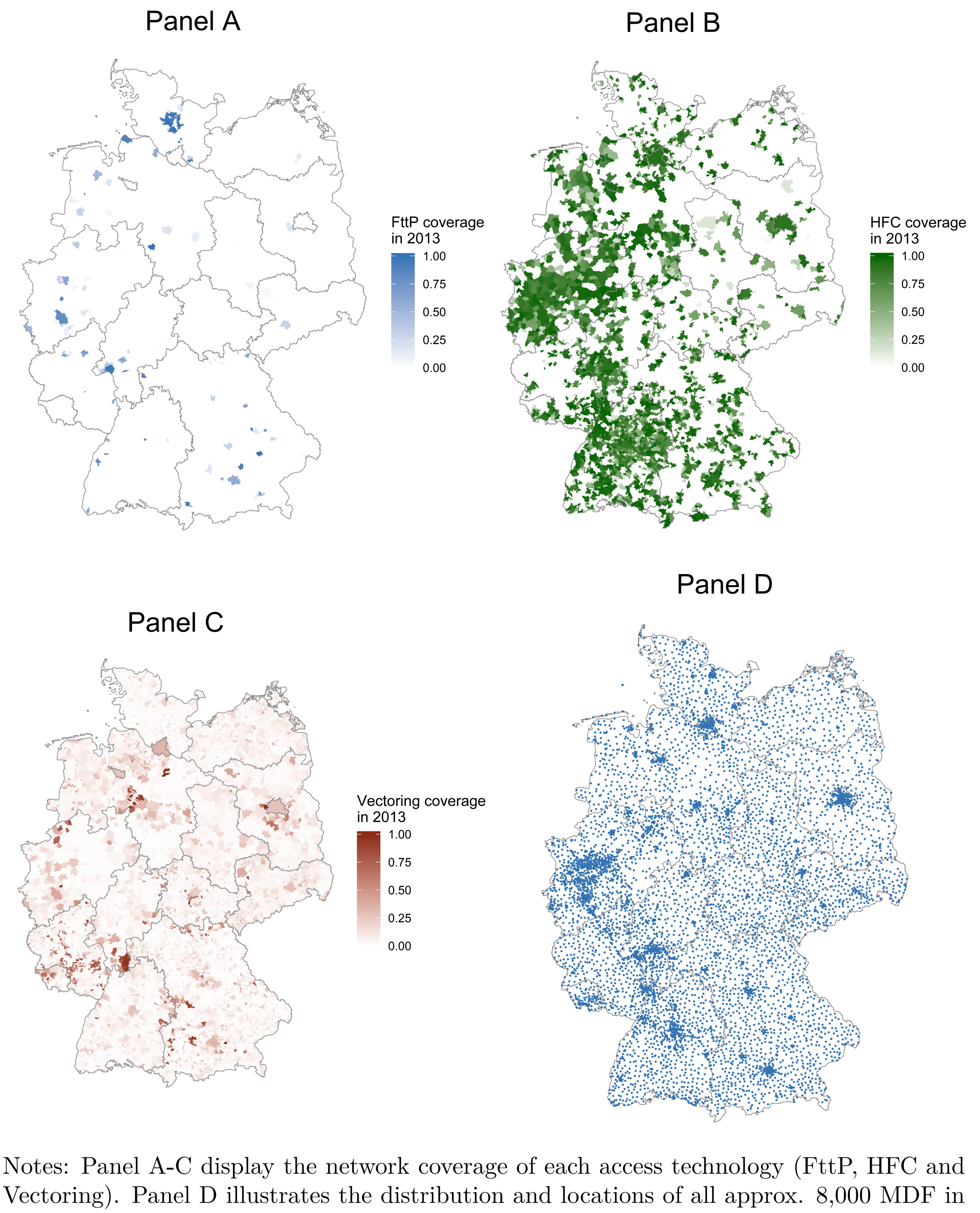
The most ubiquitous technology in Germany is the legacy copper network, upon which hybrid technologies are based. These are *Very High Data Rate DSL (VDSL)* and *VDSL2-Vectoring (Vectoring)*, which employ fiber up to intermediate network nodes - the so called cabinets - on the copper based local loop. In addition, Vectoring requires special equipment in the cabinets serving as junctions between fiber and copper double wires which filter out additional interference in the wire. The DSL architecture is based on the historical German PSTN, causing it to be near-ubiquitous since the connection of a household to a telecommunications network is a universal service in Germany. Coverage, therefore, is around 99.9 percent and the technology is the least expensive to roll out as it relies on the existing legacy network for the most complicated and costly part of the local loop, the household access.

However, both architectures suffer from the main shortcoming of copper wires: The higher the frequency of the transmitted signal (and thus connection bandwidth), the shorter the operating distance. VDSL lines provide download speeds close to 50 Mbit/s while Vectoring offers up to 100 Mbit/s downlink over short distances. The maximum operating distance lies at roughly 550m around accessed cabinets, whereas signal strength deteriorates rapidly beyond this. Hence, the upgrade potential of the copper based local loop is limited compared to other architectures. Although the next Vectoring generation G.fast will offer up to 800 Mbit/s over short distances (100m) split in down- and uplink and thus achieve the postulated 100 Mbit/s target, a copper

[5] The German CATV networks were owned by the Deutsche Telekom prior to market liberalization. From 2000 to 2003, Deutsche Telekom sold the CATV infrastructure sequentially in the form of regional sub-networks. From 2013 to 2017, the German CATV were owned by Kabel Deutschland and Unitymedia, which offered regionally differentiated HFC connections. By 2019, both firms - and thus the majority of the historical CATV infrastructure - are owned by Vodafone.

[6] DOCSIS is an abbreviation for Data Over Cable Service Interface Specification and refers to a transmission standard developed by CableLabs, a research lab founded by American cable operators. The European transmission standards (EuroDOCSIS) are based on these but are modified to the European CATV networks which use 8 MHz channel bandwidth compared to the American 6 MHz. However, there are no notable differences regarding downlink and uplink between the two.

Figure 1.1: Network coverages in July 2013 - levels of FttP, HFC & Vectoring



Notes: Panel A-C display the network coverage of each access technology (FttP, HFC and Vectoring). Panel D illustrates the distribution and locations of all approx. 8,000 MDF in the German access network.

based access technology cannot offer reliable and widespread upgrade potential towards Gigabit. Under the EC regulation and in long-term consideration it can therefore only serve as a bridging technology towards a pure fiber-based FttP network.

Vectoring is deployed predominantly by the Deutsche Telekom since the Bundesnetzagentur permitted its use in 2013. At the start of our observational period, 96,75 percent of German municipalities were connected by a VDSL based technology offering 50 Mbit/s downlink or more (Vectoring). Panel C of Figure 1.1, once again, displays the geographical deployment pattern.

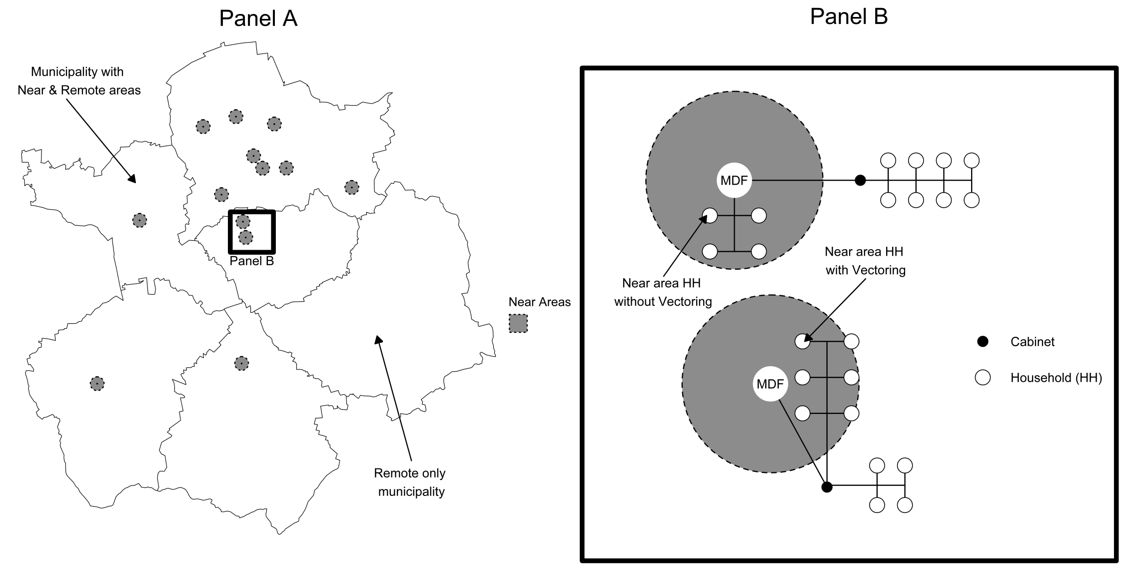
1.3.2 Identification

With the sequential introduction of Vectoring into the German telecommunications market, a natural experiment is provided which permits the identification of a potential causal relationship between the technology's availability and the deployment of FttP. In August of 2013, the Bundesnetzagentur (2013) initially permitted Vectoring in so called *Remote* areas, i.e. areas outside of 550 meter wire length starting from the serving main distribution frame (MDF). Vectoring deployments for households within that wiring distance of 550m from the MDF - the so-called *Near* areas - were permitted only in July 2017 (Bundesnetzagentur, 2016). This sequential introduction stemmed from technical limitations of the equipment installed in MDFs which was not interoperable with the equipment that needed to be installed in cabinets located too close to the MDF.[7] Prior to the application for Vectoring clearance, this sequential procedure could not have been anticipated by market participants. These circumstances enable the observation of *Near* areas in which 50+ Mbit/s connections could be provided only by means of FttP and HFC - as the EC target demands - and *Remote* areas in which all three technologies could be deployed. Panel A of Figure 1.2 illustrates the classification of *Near* and *Remote* areas within municipalities based on MDF placement.

We follow the common definition for *Near* areas and choose a radius of 550m around each MDF, which is a necessary approximation for the actual Vectoring availability. However, the technical limitations apply to wiring length, not aerial distance, but wiring may follow street corners or may be placed so as to access an entire block most efficiently. The "curvier" such paths, the more likely it becomes that households in the outskirts of the 550m radius defining Near areas are, in wire length, sufficiently distant from their MDF to permit Vectoring. However, only by allowing these false negatives

[7] Specifically, the equipment enabling Vectoring is the Digital Subscriber Line Access Multiplexer (DSLAM). Usually, these are installed in cabinets in the form of Outdoor-DSLAM and supply their respective catchment areas. If a MDF is located nearby, the Outdoor-DSLAM has to restrict its transmission spectrum on certain frequencies so as not to interfere with the MDF's signal. This spectral attenuation is normalized in the ITU-Standard G.997.1 and limited the applicability of Vectoring in its early form. Thus, the Deutsche Telekom decided to initially introduce Vectoring in *Remote* areas only, where the distances to the nearest MDF are sufficiently large.

Figure 1.2: MDF placement and identification



Notes: Panel A illustrates the classification of *Near* and *Remote* areas based on MDF placement as well as *Remote*-only municipalities which are not served by an MDF within their own boundaries. Panel B schematically displays the structure of the local loop. The *Near* area is defined by a 550m radius which allows for an exceptional case where the wire path is so"curvy" that households are accessible with Vectoring despite being theoretically located inside a *Near* area.

can the households outside the *Near* areas be properly defined as legally accessible and thus serve as functioning control group.[8] Panel B of Figure 1.2 displays the schematic structure of the local loop and the special case mentioned above.

The placement of MDF and thus the selection of households into *Near* and *Remote* areas rests on the historical structure of the German PSTN. That structure was determined first in the 1920s and then reshaped in the 1960s following reconstruction after the Second World War and during the German separation. Consequently, existing infrastructure, especially railways, together with population centers at the time shaped the network. Infrastructure influenced wiring paths, while the number of MDF grew with population size and remained substantially smaller in the GDR. Notably, wiring length had no impact on the quality of the offered telephone services, allowing MDF location choices to be based on structural characteristics and the technological restrictions of the time. [9] One MDF could, for example, house only a limited number of copper twin wires, which caused their number to inflate in larger cities.[10] Sparsely populated areas, on the other hand, required fewer MDFs or even none at all, shifting the location choice to questions of lots, suitable buildings and

[8]Furthermore, choosing a radius other than the 550 meters that define the technological limitation would be arbitrary. Accuracy of the measurement could only be improved if one accounts for the wire length of every individual connection. However, this data is not accessible.

[9]For reason of this exogeneity, Falck *et al.* (2014) also used the structure of the PSTN for identification purposes.

[10]A main cable from any MDF can contain up to 2,000 copper twin wires.

topographic issues. Panel D of Figure 1.1 displays the placement pattern of MDFs in Germany.

Given these relationships, it follows that municipalities with different population shares residing in *Near* areas also differ systemically in structural characteristics, necessitating a matching procedure to improve the quality of the control group comparison. Such an approach is as much precaution as it is necessary by endogeneity concerns. While today's deployment decisions cannot have influenced MDF placements 60 years - or even a century - ago, today's infrastructure roll-out might well be based on municipal characteristics. These, in turn, are likely to be time-persistent and could have influenced MDF placement at the time, which serves as selection into treatment. Consequently, despite the treatment being exogenous, it cannot be analyzed without accounting for the underlying structural characteristics. Their potential persistence could otherwise bias estimates on today's deployment effects when omitted. Population density, firm agglomeration and topographic peculiarities are all potential causes for such a bias. In conclusion, we chose to augment the identification by conducting a propensity score matching based on the variables best predicting MDF placement (see Section 1.5.2).

1.4 The Data

1.4.1 Broadband data

Infrastructure data is sourced from the *Breitbandatlas*, a database funded by Germany's federal government collecting information on household access to broadband technologies. Network operators voluntarily communicate to the database the share of accessed households and available speeds per technology in a given area. This data is provided on an aggregated basis.[11] All operators' offers are accumulated into the share of all households connected to either a certain speed or technology. Speeds are sorted into specific ranges, namely: ≥ 1, ≥ 2, ≥ 6, ≥ 16, ≥ 30 and ≥ 50 Mbit/s of which the last is used in this analysis because it is feasible only with Fiber, HFC and Vectoring. The most finegrained aggregation level in the data is that of municipalities, providing about 11,000 observational units for Germany.

For identification of the Vectoring-specific regulation (see Section 1.3.2), the municipality coverages were split into *Near* and *Remote* areas using virtual circles of 550m radius around the geographical positions of all main distribution frames. Of Germany's 11,187 municipalities in the set, 4972 possess MDF within their boundaries and thus

[11]Note that the data used in our analysis was provided by the TüV Rheinland, which had administered the *Breitbandatlas* until December 2018. AteneKOM has since assumed that role, but informed us that they had not received the historical data from TüV Rheinland. For this reason, our data is - to our knowledge - no longer accessible from the *Breitbandatlas*.

comprise *Near* and *Remote* areas, whereas 6211 do not and are classified as *Remote*-only. A further four municipalities are small enough to not surpass their respective *Near* area boundaries. Technology information per municipality type is summarized in Table 1.1.

Table 1.1: Average coverages by technologies

Municipality	Count	Fiber.2013	Fiber.2017	HFC.2013	HFC.2017	Vec.2013	Vec.2017
Near-only	4	0	0	0.078	0.0823	0.0954	0.1162
Remote-only	6211	0.0118	0.0568	0.1303	0.1538	0.0935	0.3206
Both: *Near*	4972	0.0075	0.0279	0.3582	0.4157	0.0631	0.2716
Both: *Remote*	4972	0.0066	0.0274	0.2826	0.322	0.0589	0.3173
With FttP Expansion:							
Near-only	0	-	-	-	-	-	-
Remote-only	622	0.1087	0.5586	0.15	0.1625	0.099	0.2929
Both: *Near*	637	0.0588	0.2174	0.5536	0.5994	0.0967	0.3943
Both *Remote*	637	0.0516	0.2141	0.4437	0.4741	0.0827	0.4593

Notes: The Average coverage quotas for all broadband technologies in municipalities are shown for *Remote*-only, *Near*-only and *Near & Remote* municipalities. The latter group is split into its two areas, but prefixed with "Both" for identification. The second part of the table shows the average coverages for all municipalities with positive FttP expansion during the observation period.

The timeframe covered in the data is that between December 2013 and June 2017, as this is the period for which the technological restrictions needed for the identification strategy were in place. Previous data is non-comparable because Vectoring had not yet been permitted, whereas Vectoring is universally feasible from a legal standpoint afterwards.[12] Hence, the choice of any other period would include a structural break invalidating the natural experiment.

The three and a half years covered in the treatment period are also sufficient to accommodate planning cycles and actual deployment, that is, for expansion to occur and treatments to show an effect.[13] However, expansion is still slow. Of all municipalities, only around ten percent receive any investment in FttP. Of those, *Remote*-only areas exhibit, on average, 56 percent of their households covered, while municipalities with MDFs receive coverage of around 21 percent by December 2017.[14] For the whole

[12]Additionally, the period from July 2017 to December 2018 is too short to observe significant expansion unrelated to projects ongoing in the treatment period.

[13]Existing changes in FttP coverage - the most costly and time-consuming technology to roll-out - underline this assumption (see Table 1.1), although expansion is still slow.

[14]Note that median values for expansion in municipalities with both areas are substantially smaller, at 5 and 6 percent for the two areas. This reflects the decrease in deployment intensity for larger municipalities on one hand and the high coverage shares for small, primarily *Remote*-only ones. Generally speaking, coverage changes are always subject to size differences between observation units. In our case, a given number of accessed households will translate to a larger coverage change for smaller municipalities than for large ones. However, observing households instead would by no means im-

of Germany, average coverage drops to 5.7 and 2.7 percent, respectively, stressing the slow speed of FttP expansion. The largest increases in coverage can be observed for Vectoring. Notably, an increase in HFC coverage is also observed, but owed not to physical deployment in the ground but to upgrades of existing systems.

1.4.2 Municipality data

The supply of broadband connections and the underlying investment decisions are likely based on market size and (presumed) willingness to pay. Given the high fixed costs of deploying fiber networks, a sufficiently large uptake and adoption of those services is necessary to recover costs. The uncertainty regarding these profits very likely constitutes a major cause for the slow expansion of FttP. More importantly, alleviating or reducing these risks will be paramount to network operators. In lieu of the network operators' actual calculations, municipality characteristics are the best approximation for them. Population and its composition are market size attributes, whereas information on the topology or urbanization structure of a given municipality provide insight into cost factors and the general accessibility. In particular, neighboring commercial centers - requiring their own unrelated fiber accesses - or new residential construction would influence coverage decisions for existing housing.

German municipalities (*Gemeinden*) provide information on their population, use of area and related statistics in the *Regionalstatistik* database. Data for 2013 is used to align with the start of the observation period, whereupon expansion decisions would have been based.[15] Average statistics for some key variables are provided in Table 1.2. *Remote*-only municipalities are smaller in terms of population, area and industry. This is a direct consequence of the original placement of MDF in alignment with existing infrastructure and population centers, as noted in Section 1.3.2.

1.4.3 Subsidies & Bavaria

To measure the impact of direct government aid on FttP deployment we use data on two broadband subsidy programs, one by the federal state of Bavaria and a second by the federal government itself. Funding from the latter was often spread out across

prove results since that measure suffers from the reverse of that issue - it allows no inference on the intensity of that expansion within the constraints of the given municipality, while coverage change does. Moreover, coverage is the policy-relevant measure.

[15]Note that data is scarce or non-existing for a small number - less than one percent - of mostly small municipalities, which drop out of the sample. Additionally, some of these municipalities have been merged with others, changing unique identifiers or creating entirely new ones. For this reason, we drop the ambiguously defined municipalities, which seems preferable to the inclusion of erroneous data; especially since their modifiers are at times not consistent in the broadband data either. Conveniently, the municipalities in question do not experience any FttP expansion.

Table 1.2: Mean municipality characteristics

Municipality	Count	Popul. (in 10,000)	Age (in years)	Density (in $100/km^2$)	Area (in km^2)	Houses (absolute)	Indust. Area (in km^2)
Near & *Remote*	4972	1.46	44.54	2.7017	52.2989	3205.41	0.5973
Remote-only	6211	0.14	44.28	1.1229	15.1305	430.33	0.0612

Notes: Averages for selected municipality characteristics with potential relevance for broadband expansion. Statistics are displayed separately for *Remote*-only municipalities and those consisting of both area types (*Near* & *Remote*).

entire administrative districts and skewed towards more populated regions.[16] Bavaria's subsidies in contrast have a similar volume to the federal program, but for the state and its 2,000 municipalities alone. Additionally, the funding - especially in the first years - is directed towards less populated, more rural municipalities and is consistently assigned to a specific municipality that applied for it. For a comparison between federal and Bavarian funding choices, see Table 1.3. Bavaria provides a detailed, publicly available database listing all funded projects and specifying allocation of money, volume, operator (responsible for network installation) and technology deployed. This program, started in 2013, is the only one of such scale and detail in Germany. The specification of the funded technology is a distinct advantage over the federal data, because it allows to assess a technology-specific deployment effect by distinguishing between FttP-specific funding and other deployment projects. To account for the aforementioned planning and construction cycles, we only consider deployment projects that had been approved by the end of 2015. Figure 1.3 displays the geographical distribution of the funding associated with this selection of projects.

1.5 The Model

The empirical strategy addresses, in turn, our three research questions regarding FttP expansion. First, where it does occur, second, to which extent, and third, how policy affect these outcomes. The first and second translate to the extensive and intensive margin of expansion, which are driven by supply side characteristics and demand indicators like deployment costs and existing legacy networks. After identifying these structural determinants, we assess two policy interventions, that is, technology restrictions and subsidies. The methods and models used for this process are explained here.

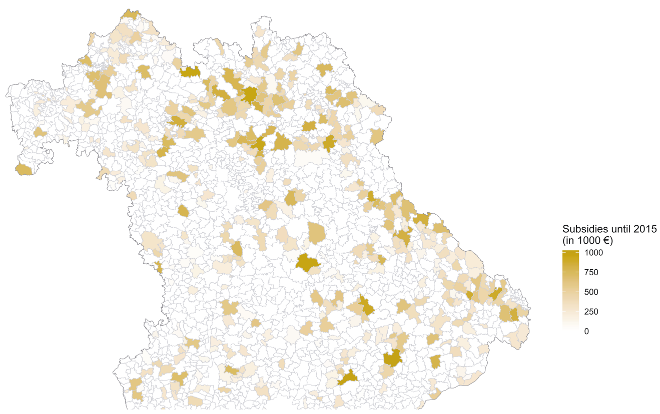
[16] In those cases when subsidies were allotted to entire districts, the total amount of subsidies was assigned to the corresponding municipalities according to their population- or area-weighted shares. Due to the inherent inaccuracy of this procedure, federal subsidies were also filtered to include only those assigned directly to specific municipalities in the first place.

Table 1.3: Subsidy statistics

Bavarian subsidies	Count	Avg.sum (in 1000 €)	Population (in 10,000)	Density (in 100/km^2)
No FttP-Funding	1986	0	0.601	1.85
FttP Funding	142	405.54	0.466	1.32
Federal Subsidies				
No Funding	10882	0	0.629	1.7565
Funding	301	2,656.70	3.8614	3.0152

Notes: Averages for Population variables of subsidized municipalities. In the federal subsidy scheme, any funding directed at a specific municipality was included. The Bavarian set is restricted to funding for projects approved before 2016 and those specifically including FttP deployment.

Figure 1.3: Bavarian subsidies accumulated until 2015



Notes: Geographical distribution of accumulated FttP funding originating from the Bavarian subsidy program. All payments of the years 2013, 2014, and 2015 were considered in the accumulation.

1.5.1 FttP expansion

Extensive Margin FttP deployment at the extensive margin is defined as the probability of a given municipality receiving FttP access as the variable of interest. This probability is a suitable measure to assess supply side considerations and the effectiveness of policy measures, although it is aggregated over operators and investments are only observed by proxy of their resulting change in coverage.

To this end, an operator's decision - whether to access a municipality or to expand an existing network - is based on determinants from five categories: technology (T), market size (Y), accessibility (X), subsidies (S) and *Länder*-specific characteristics (L). Technology T comprises variables of both competing technologies, HFC and Vectoring. Market size Y addresses the attractiveness of a municipality in terms of its population and the number of residential buildings. Average income and population age are also included here, serving as proxies for consumers' willingness to pay. Wealthier people can more easily afford price premiums for higher bandwidths and younger people are - in theory - more interested in data-intensive services. Accessibility X covers cost drivers for expansion projects, such as population density, new residential construction, total and industrially used area. The number of MDF within a given municipality is also included in this category. Because the MDF are already connected to the upper network layer via fiber, a higher density implies a more fiber-permeated municipality and a smaller need for new wiring. Subsidies S include variables of the federal and Bavarian subsidy programs. *Länder* fixed effects (L) are added to account for regional differences in market structure or construction regulations, but also for issues of ground composition and terrain. They also capture intangible factors such as differences in state-level policy and laws or broader trends stemming from Germany's East-West separation.

Subsets from these categories which are used in the extensive margin equation are indexed with E. They constitute the set of explanatory variables in the following logit model on the binary FttP investment decision for each municipality.[17]

$$Prob(\text{FttP.Exp} = 1 | X_E, Y_E, T_E, S, L) = f\left(X_E'\alpha_E, Y_E'\beta_E, T_E'\gamma_E, S'\delta_E, L'\zeta_E\right) \tag{1.1}$$

Intensive Margin The dependent variable used for FttP expansion at the intensive margin is the change in coverage share from the start of the observation period to its

[17]Other subsets of the characteristics are used outside of the main specification in robustness checks. Note also that this model is restricted ex-post to municipalities without FttP coverage in December of 2013. As elaborated upon in Section 1.6.1 of the results section, a municipality with non-zero FttP coverage in 2013 is almost guaranteed to receive further investment on account of the existing access alone. This effect is so strong that it trumps all structural factors, biasing results and necessitating this exclusion.

end: Δ FttP = $FttP.17 - FttP.13$.[18] Given that a municipality sees FttP investment, this measure accurately captures the intensity of this resulting deployment.

Technically, deployment effects at the intensive margin are estimated via OLS and with a second subset of the structural variables. The category sets for the intensive margin specification are denoted by the index I. These subsets reflect that certain structural factors are important to the binary deployment decision, but likely irrelevant to the deployment extent - and vice versa. Availability of an already existing competing infrastructure, for example, will affect deployment decisions in general, but matter for the intensity only in the case of an overlap between old and new technology. Similarly, the overall population characterizes market size, but likely does not matter for changes in the coverage for which it is effectively the denominator. Consequently, the model is defined as follows:

$$\Delta \text{ FttP} = X_I\alpha_I + Y_I\beta_I + T_I\gamma_I + L\zeta_I + u \ . \tag{1.2}$$

Additionally, the resulting difference between extensive and intensive margin models allows the use of a Heckman correction model (see Heckman, 1976, 1979), which requires such exclusion restrictions in the first step. Here, this step is the selection into FttP deployment - the extensive margin. The Heckman correction accounts for the possibiliby of non-random selection by appending a bias correction term to the second step, which reflects the potential effect of selection on the intensive margin. This bias correction is calculated via the standard deviation σ of the error term u and the inverse Mills ratio of the first stage and is defined as follows:

$$\sigma\lambda\left(X_E'\alpha_E + Y_E'\beta_E + T_E'\gamma_E + S'\delta_E + L_i'\zeta_I\right) \ .$$

1.5.2 Policy interventions

Technology Regulation As elaborated upon in Section 1.3.2, Germany's sequential introduction of Vectoring provides a natural experiment mimicking a technology-restrictive regulation, permitting the assessment of such a scheme.

However, the identification is valid not on the municipality level - as the control variables are - but for *Near* and *Remote* areas within municipalities. These differences mandate an adjustment of the data. Specifically, treatment and control groups have to be scaled up to the municipality-level required for the analysis, which is accomplished by calculating the shares of a municipality's population residing within (κ) and without

[18] As with the extensive margin specification, the analysis is restricted to first-time FttP investments (see Section 1.6.1). Thus, Δ FttP simplifies to its value at the end of the observation period, June 30 of 2017. This alters the intensive margin interpretation to the coverage chosen when a municipality is initially accessed with FttP.

Near areas $(1-\kappa)$. Treated are those municipalities which are highly affected by the technological restriction of *Near*-areas and exhibit a share κ of at least one standard deviation above the mean of the distribution of these shares ($\kappa \geq \mu_\kappa + \sigma_\kappa$). This type of municipality is classified as *Near*-heavy. Analogously, municipalities barely affected by the treatment constitute the control observations, classified as *Near*-light and defined accordingly as: $\kappa \leq \mu_\kappa - \sigma_\kappa$. All other municipalities are either of an intermediate κ and classified as *Near*-normal or *Remote*-only which naturally exhibit a share of $\kappa = 0$. Both of these latter types are excluded from the analysis regarding technology regulation because they cannot be conclusively sorted into treatment or control groups.[19] The classification of municipality types according to their *Near* share thresholds is summarized in Equation 1.3.[20]

$$\text{Municipality Type} = \begin{cases} \textit{Near}\text{-heavy} & \kappa_i \geq \mu_\kappa + \sigma_\kappa \\ \textit{Near}\text{-normal} & \mu_\kappa - \sigma_\kappa < \kappa_i < \mu_\kappa + \sigma_\kappa \\ \textit{Near}\text{-light} & 0 < \kappa_i \leq \mu_\kappa - \sigma_\kappa \\ \textit{Remote}\text{-only} & \kappa_i = 0 \end{cases} \tag{1.3}$$

Table 1.4 displays key average attributes for the four municipality types defined above. *Near*-heavy municipalities can be characterized as smaller in terms of area and population than *Near*-light (or -normal) ones. Their populations are older and possess less industrial area. Hence, treatment and control groups cannot be considered structurally equivalent ex-ante. Since those attributes might have influenced MDF placement in the past (see Section 1.3.2), selection into treatment might be non-random in this regard, necessitating a matching procedure.

Table 1.4: Average characteristics by municipality type

Municipality Type	Count	Avg. κ	Popul. (in 10,000)	Density (in $100/km^2$)	Area (in km^2)	Houses (abs.)	HVT.count (abs.)
Near-Heavy	660	0.665	0.51	2.21	26.46	1256.47	1.13
Near-Light	499	0.0741	1.96	2.42	67.94	4023.77	1.47
Near-Normal	3369	0.2629	1.69	2.97	55	3652.15	1.59
Remote-Only	6206	0	0.14	1.12	15.13	430.31	0

Notes: Comparison of key municipal characteristics by municipality type. For the thresholds defining the respective types, see Equation 1.3.

[19] *Remote*-only municipalities in particular are structurally different from municipalities with MDF and could by definition not be affected by the treatment given their lack of MDF.

[20] Note that the *Near* shares are calculated as the ratio of *Near*-area coverage to a municipality's aggregate coverage. Iteratively, all network technologies are used in this calculation to achieve the most accurate result possible. Yet for some municipalities (< 5 percent) the data is insufficiently precise and thus yields ambiguous results. These observations are dropped prior to analysis.

The procedure of choice is propensity score matching with the propensity being a municipality's probability of possessing a dense allocation of MDF and thus a substantial share of it's population residing in *Near* areas. These likelihoods are estimated via a logit model regressing this *Near*-heaviness on the more time-persistent structural attributes of German municipalities. This includes accessibility and market size characteristics such as population density, area, number of residential houses and population size, which reflect broader agglomeration trends, but also *Länder* fixed effects to capture structural differences in MDF placements resulting from the German separation and post-war federalism in West Germany.[21] The logit model used for the estimation of propensity scores is defined in Equation 1.4.[22]

$$Prob(\text{Near} = 1|LXY) = f\left(L'\alpha, \delta_1 Density, \delta_2 Area, \delta_3 Houses, \zeta_1 Population\right) \tag{1.4}$$

Based on the propensity scores from this equation, nearest neighbor matching with and without replacement is used to define suitable *Near*-light municipalities as control group for the set of *Near*-heavy treatment municipalities. This procedure is effective in reducing the differences in key variables between treatment and control group municipalities, as can be inferred from Table 1.5 in comparison with Table 1.4. Specifically, matching with replacement reduces variation between the groups by 65 to 75 percent.[23]

Table 1.5: Average characteristics of matched treatment and control group municipalities

Municipality Type	Count	Avg. κ	Popul. (in 10,000)	Density (in $100/km^2$)	Area (in km^2)	Houses (abs.)	HVT.count (abs.)
Near-heavy	539	0.66	0.51	1.37	27.08	1312.24	1.13
Near-light	173	0.07	0.86	1.46	41.42	2125.54	1.01

Notes: This table depicts average characteristics for municipalities matched with replacement using Equation 1.4, separate for treatment group (*Near*-heavy) and control group (*Near*-light) observations. The displayed covariates have been used in the calculation of the propensity scores.

Matching-relevant covariates aside, the matched subset is also balanced across federal states, largely representing treatment and control municipalities proportional to the size of the states. Schleswig-Holstein, which sees above average expansion, is slightly over-represented while the city states Bremen, Hamburg and Berlin drop out. Likewise, the two groups experience deployment roughly to the same degree as other

[21]The actual data on municipality characteristics in the 1960s when MDF were placed is, unfortunately, not comprehensive. This is due to the entire exclusion of the former GDR and incomplete data-keeping for West German municipalities. Hence, the reliance on present-day data.

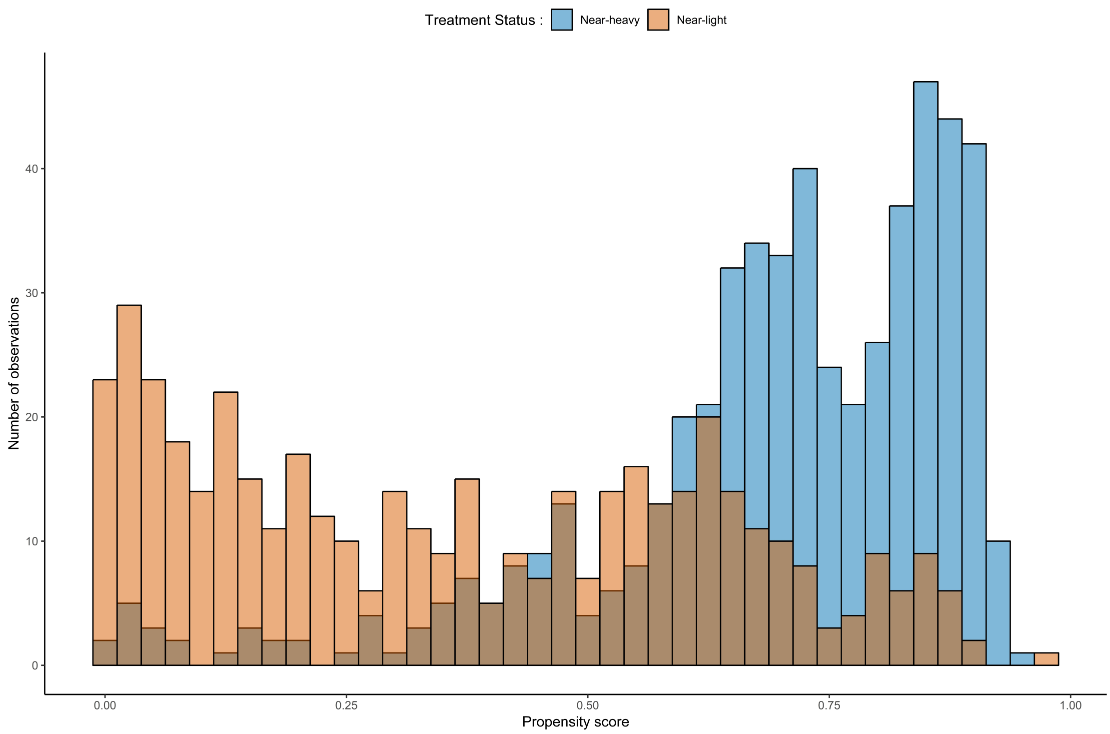
[22]For a more detailed look into the quality and choice of this specification, see Table A.7 of the Appendix.

[23]Matching without replacement performs worse, but still significantly reduces divergence.

municipality types, implying a common population with respect to actual and predicted deployment decisions.[24]

In terms of common support, the two groups have sufficient overlap for a qualified comparison (see Figure 1.4). Discrepancies do exist in the areas of higher propensity scores, pointing to limitations of the matching. But this deviance in the tails seems acceptable given the higher number of treatment than control observations and the fact that municipalities of a high predicted *Near*-heaviness are typically larger in area and smaller in population - and thus less comparable to *Near*-light municipalities. Furthermore, the matching is more a precaution against an indirect bias resulting from persistence in explanatory variables, not against selection into treatment, since MDF location and broadband expansion are decisions taken almost a century apart. Using the matched set, we calculate the average treatment effects and apply also an OLS estimation for robustness.

Figure 1.4: Area of common support



Notes: Probabilities of being *Near*-heavy for municipalities that have a high share of *Near* areas (treatment) and those with a low share of *Near* areas (control group).

Subsidies The impact of subsidies as a determinant of FttP expansion is assessed using the comprehensive program and recordings of the Free State of Bavaria. Extensive and intensive margin models are estimated equivalently to Equation 1.1 and

[24]Figure A.1 in the Appendix displays this as a collection of scatter plots for the federal states.

Equation 1.2, sans the *Länder*-dummies. Thus, the subsidies become a singular addition to an otherwise unchanged set of characteristics, permitting comparison across models and subsets.

1.6 Results

1.6.1 FttP expansion

Pre-existing FttP The first result and an ex-post restriction of the main analysis is the special status of municipalities with positive FttP coverage in 2013 ($FttP.13 > 0$), the start of the observational period. They are almost guaranteed to receive further FttP expansion during the observation period (ΔFttP > 0). Out of 311 municipalities which were already accessed with FttP, 303 received further investments into the technology between 2013 and 2017 (see Table 1.6), while the remaining eight already had high coverage. On average, these municipalities are substantially larger and more densely populated than their counterparts without FttP in 2013. Although these mean characteristics are inflated by Germany's largest cities and skewed by heterogeneity in municipalities, these general trends remain even when observing median values, which suggest a structural distinction between early adopting municipalities and all others.[25]

Table 1.6: Municipal characteristics by pre-existing FttP coverage

FttP.13$>$ 0, ΔFttP > 0	Count	FttP.13	ΔFttP > 0	Population (in 10,000)	Density (in 100/km^2)	HVT.count (abs.)
No, No	9916	0	0	0.52	1.67	0.56
No, Yes	956	0	0.295	1.41	2.3	0.96
Yes, No	8	0.696	0	0.02	0.52	0
Yes, Yes	303	0.339	0.002	5.47	5.54	2.93

Notes: Average characteristics for municipalities with and without FttP coverage in 2013 are displayed, separated into those that did (Δ FttP$>$ 0) and did not receive expansion (Δ FttP$=$ 0) during the observational period.

If early adopting municipalities were of a population distinct from all other municipalities, their inclusion in the set of the main analysis might bias results. Structural drivers of investment could no longer be identified correctly. A regression of being an early adopter on FttP expansion taking place stresses this risk.[26] Existing coverage in 2013 implies an expansion probability of near 100 percent in linear, logit and probit

[25] Median municipality characteristics relating to FttP coverage in 2013 are displayed in Table A.1 of the Appendix.

[26] Being an early adopter is captured by the dummy F2013 which takes the value 1 if FttP.13$>$ 0 and a value of 0 otherwise.

models (see Table 1.7). Given the dominance of this effect for pre-existing FttP coverage, the exclusion of all municipalities with FttP coverage in 2013 becomes necessary. Hence, the sample is reduced to municipalities not accessed with FttP by the end of 2013 (FttP.13 = 0). The following results on FttP deployment therefore have to be interpreted with respect to first-time deployment.

Table 1.7: Influence of pre-existing FttP on the probability of FttP expansion

	Linear (1)	Logit (2)	Probit (3)
		FttP.Exp [0,1]	
(Intercept)	0.09***	−2.34***	−1.35***
	(0.00)	(0.03)	(0.02)
F2013 [0,1]	0.89***	5.97***	3.30***
	(0.02)	(0.36)	(0.15)
R^2	0.21		
Adj. R^2	0.21		
Num. obs.	11183	11183	11183
Log Likelihood		-3274.07	-3274.07
Deviance		6548.15	6548.15

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: Regression of FttP.Exp solely on the existence of FttP coverage in 2013 (F2013). Note that FttP.Exp is a dummy that takes the value 1 if Δ FttP > 0 and a value of 0 otherwise. Analogously, F2013 is a dummy that takes the value 1 if FttP.13> 0 and the value 0 otherwise. The first model (1) is a linear approximation, whereas the other two are maximum likelihood estimations using logit (2) and probit (3) links, respectively. Note that existing FttP instantly raises expansion probability to 1 in all three models.

Extensive Margin FttP investment decisions at the extensive margin appear driven by elements from three of the four categories defined: technology, size and accessibility. Subsidies are insignificant on the federal level. Table 1.8 shows the estimations for the corresponding Logit and OLS regressions.[27]

In terms of technology competition, the base coverage of Vectoring in the *Near* area of a given municipality increases the likelihood of FttP expansion by 2.9 percentage points (pp) per 10 pp higher coverage (using OLS results).[28] Likewise, expansion of

[27]Robust and *Länder*-clustered standard errors have been calculated for these regressions and shown no changes in significance levels. In addition, the Appendix Table A.3 summarizes the marginal effects derived from the results of the OLS regressions. In Table A.4, marginal effects for the Logit estimations are being displayed. As they are qualitatively similar to OLS, the analysis focuses on the more robust OLS estimators. Expected probabilities of below zero or above one are also exceedingly rare, alleviating the potential shortcoming of OLS.

[28]The significant and positive effect of base Vectoring coverage in *Near* areas does not invalidate

Table 1.8: Determinants of FttP expansion at the extensive margin

Endogeneous Variable:	FttP.Exp [0,1]			
Municipality	Near & Remote		Remote-only	
Model	Logit	OLS	OLS	Logit
	(1)	(2)	(3)	(4)
(Intercept)	5.12***	0.75***	0.60***	2.89*
	(1.53)	(0.13)	(0.09)	(1.33)
Vectoring.13.r	0.96	0.06	0.16***	2.25***
	(0.68)	(0.07)	(0.03)	(0.35)
Vectoring.13.n	1.82***	0.29***		
	(0.54)	(0.06)		
Δ Vectoring.r	0.70**	0.06**	0.04**	0.55**
	(0.26)	(0.02)	(0.01)	(0.21)
Δ Vectoring.n	0.32	0.02		
	(0.30)	(0.03)		
HFC.13.r	−0.72·	−0.06·	−0.03	−0.44
	(0.40)	(0.03)	(0.02)	(0.31)
HFC.13.n	0.81**	0.07**		
	(0.30)	(0.03)		
Population	0.06	0.01*	0.01	0.31
	(0.05)	(0.01)	(0.03)	(0.50)
Age	−0.15***	−0.01***	−0.01**	−0.09**
	(0.03)	(0.00)	(0.00)	(0.03)
Density	0.01	0.00	−0.00	−0.01
	(0.02)	(0.00)	(0.00)	(0.06)
New Construction	5.15	0.46	0.48*	5.62*
	(3.51)	(0.33)	(0.21)	(2.54)
Area	0.01***	0.00***	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.01)
HVT.count	−0.10	−0.01		
	(0.09)	(0.01)		
nearby10k	0.50***	0.05***	0.09***	0.86***
	(0.15)	(0.01)	(0.01)	(0.16)
HFC.Exp.r			0.04**	0.53**
			(0.01)	(0.17)
Länder FE	YES	YES	YES	YES
Log Likelihood	-1154.21			-891.39
Deviance	2308.42			1782.78
Num. obs.	4011	4011	3808	3808
R^2		0.10	0.19	
Adj. R^2		0.09	0.19	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: Determinants are shown for municipalities with both *Near* & *Remote* areas and *Remote*-only ones. The probability of expansion in a given municipality is estimated using Logit - (1) and (4) - and OLS - (2) and (3) -, and separately for the types of municipalities due to type-specific regressors. Within type, the specifications are identical but for the method.

Remote area Vectoring in the observation period raises the FttP investment probability by 0.6 pp per 10 pp coverage increase. For *Remote*-only municipalities, results are broadly similar: a higher base coverage of Vectoring raises investment probabilities by 1.6 pp per 10 pp higher coverage and Vectoring expansion by 0.4 pp (per 10 pp change).[29] In relation to the average predicted investment probabilities of around 10 percent for *Near* & *Remote* municipalities and 8 percent for *Remote*-only ones, these effects are substantial.[30]

In contrast to Vectoring, HFC seems less relevant for FttP deployment. While the HFC base coverage in *Near* areas positively impacts investment probability by 0.7 pp per 10 pp higher HFC coverage, its impact becomes negative and insignificant for *Remote*-only municipalities. Additionally, investment into HFC is very rare, but nonetheless impacts FttP expansion in *Remote*-only municipalities positively by a 4 pp increase in probability should HFC coverage be increased.[31] Consequently, competing infrastructure appears to increase the FttP deployment probability, although that might also be a result of legacy infrastructure and its expansion signaling generally attractive deployment areas. Vectoring could, given these results, be seen as a complementary (bridge) technology.

Of the market size characteristics, population and age are significant and relevant. Per additional 10,000 people, the deployment probability increases by 1 pp for municipalities with their own MDF, implying a size advantage in FttP expansion due to the greater agglomeration of potential customers.[32] Accordingly, population is insignificant for the typically smaller *Remote*-only municipalities.[33] The average age of a population on the other hand has a negative effect amounting to a one pp reduction in expansion probability per additional year of average age. Given a lesser interest of older people into digital services such as streaming or video gaming, this result is both intuitive and a reasonable reflection of demand trends.[34]

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the identification. Recall from Section 1.3.2 that Vectoring may be feasible in the outskirts of a given *Near* area. Usually, *Near* areas are located in proximity to population centers which would make them more attractive for FttP expansion. This provides an explanation for the positive association of Vectoring coverage in *Near* areas and the probability of FttP deployment.

[29] The coefficient for *Near* area Vectoring expansion is also not significant, which reflects the ban of Vectoring in these areas and the resulting lack of variation in the data.

[30] The averages of the predicted investment probabilities are near-identical between linear and Logit models, which also fits the 10 and 9 percent of municipality types receiving investment over the observation period well.

[31] Note that only the fact of expansion happening matters, as measured by the HFC.Exp.r dummy variable. The extent is irrelevant.

[32] A part of this effect may also be stochastic. If all groups of households were equally likely to receive FttP connections, municipalities with larger populations will enjoy a greater likelihood of FttP investment on account of their above-average number of households alone.

[33] Smaller populations also exhibit a lower propensity of expansion overall, which might reflect this adverse population effect.

[34] The age effect may be slightly overstated on account of a correlation between aging populations and rural or structurally weak areas, insofar as the latter factors are not entirely accounted for by other covariates in the analysis. The broader analysis of such structural covariates is summarized in

Accessibility of a municipality is mainly characterized by cost measures. First, population density - typically considered a prime factor - is not significant for either municipality type, although its components population and area are.[35] Second, a larger area increases expansion probabilities by 0.5 pp per $10km^2$ for municipalities with MDF. This effect becomes insignificant for *Remote*-only observations, reflecting the dual nature of area: if populated, it increases investment opportunities within, but an unpopulated rural or forested area signals higher deployment costs.[36] Third, the quota of newly constructed residential buildings benefits deployment probability in *Remote*-only municipalities. For an additional percentage point of new construction, the probability of FttP expansion increases by 0.5 pp. This *Remote*-only exclusive effect corresponds to the lesser attractiveness of these municipalities and thus their higher dependence on new residential housing, requiring new fiber wiring, to cause FttP deployment.[37]

Finally, the special cases of municipalities with pre-existing FttP coverage are addressed by the dummy variable *nearby10k* which denotes whether a given municipality is in proximity to one of the excluded municipalities with positive FttP coverage in 2013.[38] This variable aims to capture a possible radiation - and source of bias - of the near-certain FttP expansion into neighboring municipalities. Its coefficient is significant and exerts a positive influence on the expansion probability. In the linear model, FttP deployment becomes 5 pp more likely for municipalities with MDF and 9 pp more likely for those without MDF. This effect can be likened to an expansion “hub” - in a loose sense of the term - wherein existing local networks branch out into their neighborhood following successful early-adoption projects.

Intensive Margin Once a municipality is chosen for FttP expansion, a network provider needs to decide on the deployment extent. That extent likewise depends upon factors subsumed under the categories technology, market size and accessibility. Table 1.9 displays the estimated regression results for FttP expansion at the intensive margin for those municipalities with and without MDF which received FttP expansion.[39]

the extensive margin specifications of Table A.2 in the appendix.

[35]In a reduced form regression on accessibility characteristics alone, population density is of relevance but this link disappears as soon as other categories are included (see Table A.2 in the Appendix).

[36]More general geographic or structural and political features are captured by the *Länder* fixed effects, which are highly relevant.

[37]Note that it cannot be determined from the data whether the expansion occurs solely to connect the new properties or acts as an initial trigger for a wider FttP deployment.

[38]The variable is computed with data from the Gemeindeverzeichnis providing the geographical centroid of a given municipality. Using these coordinates, the dummy *nearby10k* takes the value 1 when the centroid of at least one municipality with $FttP.13 > 0$ is exactly or less than ten kilometers distant from the given municipality. This threshold of ten kilometers is derived from the mean size and standard deviation of the municipalities in the set. For robustness, thresholds of 5 and 25 kilometers were also considered.

[39]For these estimates, robust and *Länder*-clustered standard errors have also been calculated, but yielded almost identical results for the standard errors. For a detailed look into the different variable

Table 1.9: Determinants of FttP expansion at the intensive margin

Endogeneous Variable:	Δ FttP	
Municipality	Near & Remote	Remote-only
	(1)	(2)
(Intercept)	1.52^{***}	1.75^{***}
	(0.37)	(0.38)
Δ Vectoring.r	-0.14^{**}	-0.23^{***}
	(0.04)	(0.04)
Age	-0.02^{*}	-0.02^{**}
	(0.01)	(0.01)
Income p. capita	$-0.00^{\cdot}$	0.00
	(0.00)	(0.00)
Density	$-0.01^{\cdot}$	-0.02
	(0.00)	(0.01)
New Construction	$-1.38^{\cdot}$	-0.29
	(0.77)	(0.70)
Area	-0.00^{***}	-0.01^{**}
	(0.00)	(0.00)
Länder FE	YES	YES
R^2	0.34	0.53
Adj. R^2	0.31	0.51
Num. obs.	409	346

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Determinants of intensive margin FttP expansion in municipalities with *Near* & *Remote* areas in (1) and *Remote*-only in (2), contingent on them having seen positive FttP deployment in the extensive margin between 12/2013 and 06/2017, that is: FttP.Exp = 1. The endogenous variable (Δ FttP) is the change in FttP coverage within a given municipality.

From the set of network technology variables, only Vectoring remains significant and relevant for the intensive margin. Base levels and changes in HFC have no explanatory power, whereas the change in Vectoring coverage negatively impacts FttP intensity by 1.4 pp per 10 pp change in coverage for municipalities with MDF. For *Remote*-only ones, this effect increases to 2.3 pp. Both results imply a rather substitutive than complementary effect of Vectoring for FttP expansion, which would support the EC's interpretation. Hence, a simultaneous roll-out of Vectoring appears to partially foreclose - in a loose application of the term - the respective area to FttP deployment. On first glance, this interpretation may appear contrary to the positive effect of the Vectoring base coverage at the extensive margin, but likely implies a more complex relationship: Early Vectoring adoption signals an attractive market, but competition in the form of a high expansion of Vectoring coverage curtails the areas in which FttP could be provided profitably. The effect of Vectoring is thus ambiguous. An already high Vectoring coverage may cause FttP investment as a competitive reaction, but if Vectoring is further extended during this period, it simultaneously limits the intensity of FttP deployment. Hence, the Vectoring base coverage and the coverage increase seem to capture two different dimensions in the technology competition between these two infrastructure types.

Of the market size characteristics, the average population age and average available income matter for FttP expansion at the intensive margin. Again, an older population limits the market potential of FttP based services. Available income, however, is barely significant but its coefficient has a negative sign, which is implausible and remains puzzling to the authors.[40]

Accessibility measures seem to be most relevant for the deployment extent. In contrast to the extensive margin results, population density is weakly significant for municipalities with *Near* areas, its coefficient implying a 1 pp reduction at the intensive margin for an additional 100 inhabitants per square kilometer. Density can thus be thought of as a cost driver: A denser population implies a higher degree of urbanization and households requiring connection, complicating construction procedures. Similarly, a municipality's area exhibits a negative effect on the intensive margin ranging from 0.1 pp less coverage expansion per 10 km^2 for municipalities with *Near* areas to 0.5 pp less expansion for those without. As a greater area implies longer cable lengths to connect the households in question, construction likewise becomes more expensive.[41]

New residential housing also has a negative impact on the intensity of FttP expansion, although it is significant only at the 10%-level and for municipalities with

categories and their effects, see Table A.5 in the Appendix.

[40]The North-South divide in Germany provides a potential explanation for this effect, in that the wealthier but often more remote and more rural areas of South Germany appear to receive less FttP expansion.

[41]Controlling for the proximity to a municipality with FttP in 2013 does not alter results, for this reason the dummy variable of *nearby10k* is not included in the final specification.

Near areas. This reflects the positive effect for *Remote*-only municipalities already found in the extensive margin because new construction is naturally connected to the communications infrastructure via FttP, thus providing expansion of FttP where it would not have occurred otherwise. Larger municipalities would be less dependent on new construction with regards to FttP expansion due to their structural advantages, which would also result in small shares of new construction relative to existing housing. Smaller municipalities, however, might only see FttP investment for new construction, suggesting a lesser attractiveness of a municipality with a larger share of new construction and, hence, the negative sign.

Lastly, as stated in Section 1.5.1, these results rely on the assumption that the intensive margin effects are independent from selection into expansion. This is tested using a Heckman two-step procedure, which yields similar results to OLS and thus implies that selection is not an issue.[42] In consequence, the first two main results regarding FttP expansion are summarized below.

Result 1: Structural determinants of market size and accessibility are relevant for the likelihood of FttP deployment. Of those, a population's age is of major importance.

Result 2: Technology competition from Vectoring has opposing effects. While a high Vectoring base coverage appears to signal attractive markets for FttP deployment and hence increases deployment probability, a simultaneous expansion of Vectoring coverage decreases the deployment intensity of FttP.

1.6.2 Policy interventions

Technology Regulation The previous analysis produces significant, yet ambiguous effects of Vectoring on FttP deployment. However, these are only correlations and not necessarily reflective of causal relationships. Utilizing the identifying restrictions in the German telecommunications market (see Section 1.3.2), the interactions between these two technologies can be defined more clearly. The matching procedure presented in Section 1.5.2 generates a set of 539 treatment (*Near*-heavy) and 173 control observations (*Near*-light). These match one another more closely not only in terms of treatment probability but also in other relevant structural characteristics.[43] If the matching is

[42]The regression results are displayed in Table A.6 in the Appendix. Notably, per-capita income loses significance when accounting for a potential selection. However, *Länder* fixed effects cannot be used in the Heckman approach due to technical issues with the low number of municipalities with investment for smaller federal states, thus restricting the approach to such a degree that it would not be as useful as the main specification. Due to its qualitatively similar results, this is not necessary either.

[43]Due to this desired similarity in observations and resulting lack of variance, most variables with previously significant coefficients in the extensive and intensive margin specifications become insignificant in a supplemental regression based on the matched subset (see Table A.8 in the Appendix).

conducted without replacement, 451 treatment and control units each remain in the dataset. For both these sets, mean values for technology and municipality characteristics are provided in Table 1.10. Notably, the predicted probabilities for expansion are similar for treated and non-treated municipalities.[44] This aspect, alongside their similarity in structural characteristics, supports the parallel trends assumption required for assessing the treatment effect.

Table 1.10: Mean characteristics for matched municipalities

Municipality Type	FttP.Exp= 1	Count	Δ FttP	P(FttP.Exp= 1)	Population (in 10,000)	Houses (abs.)	Δ Vectoring.r
Municipality statistics, matching with replacement:							
Near-heavy	No	488	0	0.08	0.51	1308.7	0.19
Near-heavy	Yes	51	0.37	0.2	0.48	1346.12	0.23
Near-light	No	156	0	0.09	0.81	2085.65	0.25
Near-light	Yes	17	0.31	0.19	1.33	2491.59	0.29
Municipality statistics, matching without replacement							
Near-heavy	No	412	0	0.08	0.53	1348.44	0.19
Near-heavy	Yes	39	0.38	0.18	0.48	1333.41	0.25
Near-light	No	406	0	0.11	1.18	3246.67	0.3
Near-light	Yes	45	0.2	0.2	1.66	4376.44	0.33

Notes: Summary statistics for the matched treatment (*Near*-heavy) and control (*Near*-light) subset based on propensity scores. Sample means for the technology variables of interest as well as other municipality characteristics are provided for both matching with and without replacement.

The treatment has a significant impact only in the subset generated by matching without replacement (see Table 1.11 for sample means and p-values). Therein, treated municipalities experience significantly more FttP expansion at the intensive margin. However this result comes with a caveat since this subset suffers from a deterioration in matching quality. Structural characteristics and predicted extensive margin probabilities differ more substantially in the matching subset when matched without replacement, yielding a control group of, on average, larger and more populous municipalities (see Table 1.10). That size difference might be partially responsible for the lower change in coverage of the control groups. Since coverage as a measure of expansion is relative to the number of households, it is more costly to achieve a given coverage increase in larger municipalities than it is in smaller ones (see also Table 1.1). All of this limits the validity of the results for matching without replacement.

In conclusion, a technology selective regulation, mimicked by the de-facto ban of Vectoring in *Near*-areas, seems to have no measurable impact on the decision to invest into FttP deployment and - at best - a small one on the intensity of such deployment.

Rationales for the null effect at the extensive margin could be twofold. First, the decision to invest depends primarily on market size and accessibility characteristics as

[44] The predicted deployment probabilities stem from the main extensive margin specification in Section 1.6.1 and are displayed in column 5 of Table 1.10.

Table 1.11: Average treatment effects

		Matching			
		With replacement		Without replacement	
		Treat	Control	Treat	Control
Ext. Margin	Count:	539	173	451	451
	FttP.Exp= 1:	0.095	0.098	0.086	0.100
	$Pr(>\|t)$	0.888		0.4923	
Int. Margin	Count:	51	17	39	45
	Δ FttP:	0.367	0.306	0.382	0.205
	$Pr(>\|t)$	0.573		0.040*	

Notes: Mean treatment comparisons via symmetric t-test for the extensive and intensive margins of FttP expansion. Respective group means as well as test results are provided separate for matching with replacement and without.

well as the coverage of already existing network technologies. A restriction on Vectoring affects solely the last of these aspects, and only for the less capable technology. Second, Vectoring in Germany is deployed almost exclusively by the Deutsche Telekom, which might use the technology to respond to FttP expansion or HFC offerings by its competitors. This simultaneity might drive the positive correlation of change in Vectoring coverage and FttP expansion at the extensive margin.

The limited influence of the treatment - both in significance and relevance - on the intensive margin is not surprising given the previous intensive margin results. The detrimental effect of Vectoring expansion on FttP deployment intensity is, in fact, reinforced by the results of the technology-restrictive regulation beyond correlation alone. It seems reasonable to assume that Vectoring exhibits competitive pressure on FttP network providers, thus limiting the intensity of their deployments. A policy specifically alleviating that pressure would reasonably be effective - if at all - at the intensive margin.

Subsidies Repeating the analyses of Section 1.6.1 for the Free State of Bavaria permits the inclusion of its comprehensive subsidy program on the municipality level. Table 1.12 displays the estimated regression results for the extensive margin deployment probability of FttP for Bavarian municipalities.

This subsidy program appears to be very effective. Every additional 100,000 Euro of funding for expansion including FttP projects increases the probability of FttP investment by three pp.[45] For *Remote*-only municipalities, the effect increases to four

[45]Bavaria also subsidized Vectoring deployment projects which would have included Vectoring solutions. A regression of such, non-FttP subsidies on expansion probabilities provides no significant effects. This is the expected result and provides no support for the ladder-of-investment hypothesis, although the observation period is admittedly rather short for that evolution to occur.

Table 1.12: Bavaria subsample: Determinants of FttP expansion at the extensive margin

Endogeneous Variable:	FttP.Exp [0,1]			
Municipality	Near & Remote		Remote-only	
Model	Logit	OLS	OLS	Logit
	(1)	(2)	(3)	(4)
(Intercept)	−3.35	−0.08	−0.43$^{\cdot}$	−11.62*
	(3.92)	(0.24)	(0.22)	(4.60)
Vectoring.13.r	2.03	0.18$^{\cdot}$	0.24***	3.40***
	(1.35)	(0.11)	(0.05)	(0.76)
Vectoring.13.n	1.39	0.22$^{\cdot}$		
	(1.38)	(0.12)		
Δ Vectoring.r	−0.16	−0.01	0.06*	1.23*
	(0.63)	(0.05)	(0.03)	(0.57)
Δ Vectoring.n	1.74*	0.16**		
	(0.74)	(0.06)		
HFC.13.r	−1.16	−0.08	0.03	0.59
	(1.04)	(0.08)	(0.04)	(0.72)
HFC.13.n	1.20$^{\cdot}$	0.08		
	(0.73)	(0.05)		
Population	0.22	0.02	−0.01	−0.24
	(0.22)	(0.02)	(0.06)	(0.89)
Age	0.00	0.00	0.01$^{\cdot}$	0.17
	(0.09)	(0.01)	(0.01)	(0.10)
Density	0.01	−0.00	−0.00	−0.06
	(0.05)	(0.00)	(0.01)	(0.17)
New Construction	−16.36	−0.81	0.03	−0.21
	(11.66)	(0.63)	(0.48)	(11.31)
Area	0.01**	0.00**	0.00$^{\cdot}$	0.02$^{\cdot}$
	(0.00)	(0.00)	(0.00)	(0.01)
HVT.count	−0.54	−0.04		
	(0.42)	(0.03)		
nearby10k	0.93**	0.08***	0.07***	1.21***
	(0.31)	(0.02)	(0.02)	(0.34)
Funding until 15	0.28***	0.03***	0.04***	0.38***
	(0.06)	(0.01)	(0.01)	(0.08)
HFC.Exp.r			−0.01	−0.21
			(0.02)	(0.45)
Log Likelihood	-224.36			-169.23
Deviance	448.71			338.47
Num. obs.	942	942	905	905
R^2		0.09	0.08	
Adj. R^2		0.08	0.07	

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: Determinants are shown for municipalities with both *Near* & *Remote* areas and *Remote*-only for the subsample of Bavaria. This table is a Bavaria-only replication of Table 1.8. The probability of expansion in a given municipality is estimated using Logit - (1) and (4) - and OLS models - (2) and (3) -, and separately for the two types of municipalities due to type-specific regressors. Aside from the method applied, the specifications are identical for each type.

pp. Given that only five percent of Bavaria's *Remote*-only municipalities and eight percent of its *Near* & *Remote* municipalities see any FttP expansion, this relates to an increase in expansion probability by 12.5 to 40 percent for a subsidy of 100,000 Euro.

However, these results cannot be translated directly to Germany as a whole since Bavaria has a somewhat non-representative structure. It consists of few large cities or comparable population centers and a large number of smaller towns and surrounding rural areas. Market size is not as relevant due to the homogeneity of the localities and the exclusion of large cities on account of already existing FttP in 2013. Accessibility characteristics, on the other hand, are similar in significance and strength.

Technological factors are also less relevant. The coefficients for the HFC base coverage and investment into it are insignificant, which likely results from the technology being less prevalent in Bavaria, limiting variation. Vectoring - both base coverage and expansion - is more relevant and significant for *Remote*-only municipalities, but only Vectoring expansion in *Near* areas matters for *Near* & *Remote* municipalities. These findings are reflective of the lower levels of broadband expansion and coverage in Bavaria compared to the whole of Germany.

Subsidies also have no significant effect with respect to the intensive margin.[46] Their coefficient is, however, negative which would seem logical as municipalities expanded only on account of subsidies would likely be less attractive than those expanded without subsidies. The Bavarian state's tendency to provide subsidies especially to smaller, less densely populated municipalities supports this interpretation.

We summarize the main results regarding policy interventions below:

Result 3: A deployment regulation restricting Vectoring use is ineffective in increasing the likelihood of a given municipality being accessed with FttP. Deployment intensity is not adversely affected by the regulation.

Result 4: Subsidies targeted specifically at local FttP deployment projects are effective in increasing the deployment likelihood. An additional 100,000€ in funding increases that probability by 3 to 4 pp.

1.7 Conclusion

Upgrading the telecommunications infrastructure to match digitalization requirements is a prominent aim of national policies. Governments attempt to shape and promote the transition from legacy copper networks to FttP architectures by setting national

[46]Table A.9 displays the corresponding regression results and compares them to the results for all of Germany. *Remote*-only municipalities are not considered in the table because too few of them received subsidies in Bavaria for an OLS regression to provide consistent results.

goals and deployment guidelines, among others. The actual infrastructure provision is carried out on the local level within specific deployment projects, organized under the policymakers' broad agendas, though.

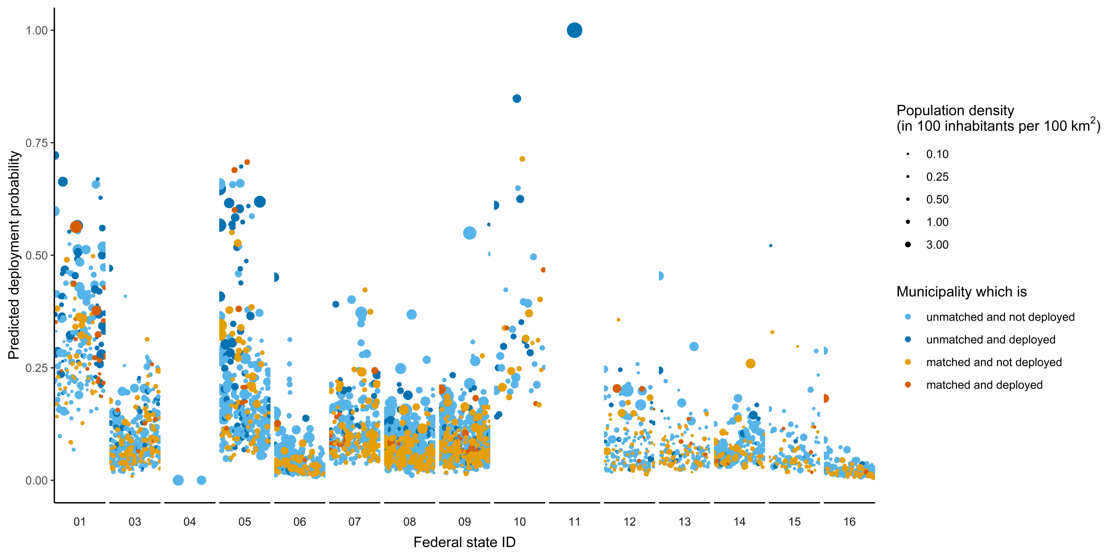
This study aims to sheds light on determinants and the effectiveness of policy interventions that influence FttP deployment on a micro-level. Local and structural conditions are found to be decisive supply-side factors in explaining the locations chosen for FttP deployment and the intensity of that expansion. Population size and average age, the share of newly built residential housing as well as municipal areas are strongly associated with the probability for FttP deployment. Additionally, municipalities with early FttP adoption emit a spillover effect on their neighbors and increase their chance of receiving FttP access. Local competition from other network infrastructures, namely Vectoring and HFC, has more ambiguous effects. While a higher base coverage is associated with a more likely FttP deployment, an increase in Vectoring coverage reduces the deployment extent.

Against these structural factors, a technologically restrictive policy ruling out Vectoring is found to be generally ineffective. Neither FttP expansion at the extensive margin nor at the intensive margin reacts to the deployment restrictions. The removal of Vectoring as a competing infrastructure shows no effect. In contrast, state intervention in the shape of subsidies are effective. An additional funding of 100,000€ increases the FttP deployment probability of a Bavarian municipality by 3 to 4 percentage points, corresponding to a 12.5 to 40 percent change given the average deployment probability. However, this only applies to funding for FttP-specific projects.

Therefore, the main challenge for policymakers in shaping the infrastructure upgrading process is overcoming the structural conditions that determine the FttP rollout. Subsidies targeted directly at specific, local FttP projects are able to overcome these structural disadvantages. A general technologically restrictive regulation, on the other hand, is not sufficient. Our results advocate for an increased focus on structural support schemes in the vein of Bavaria's subsidy program. Together with the FttP spillover effects radiating from already fiber-accessed municipalities, a geographically scattered distribution of these subsidies, focusing on local centers, could be optimal. These "subsidy hubs" might decrease costs of FttP deployment for the smaller neighboring municipalities, reinforcing the positive deployment effect.

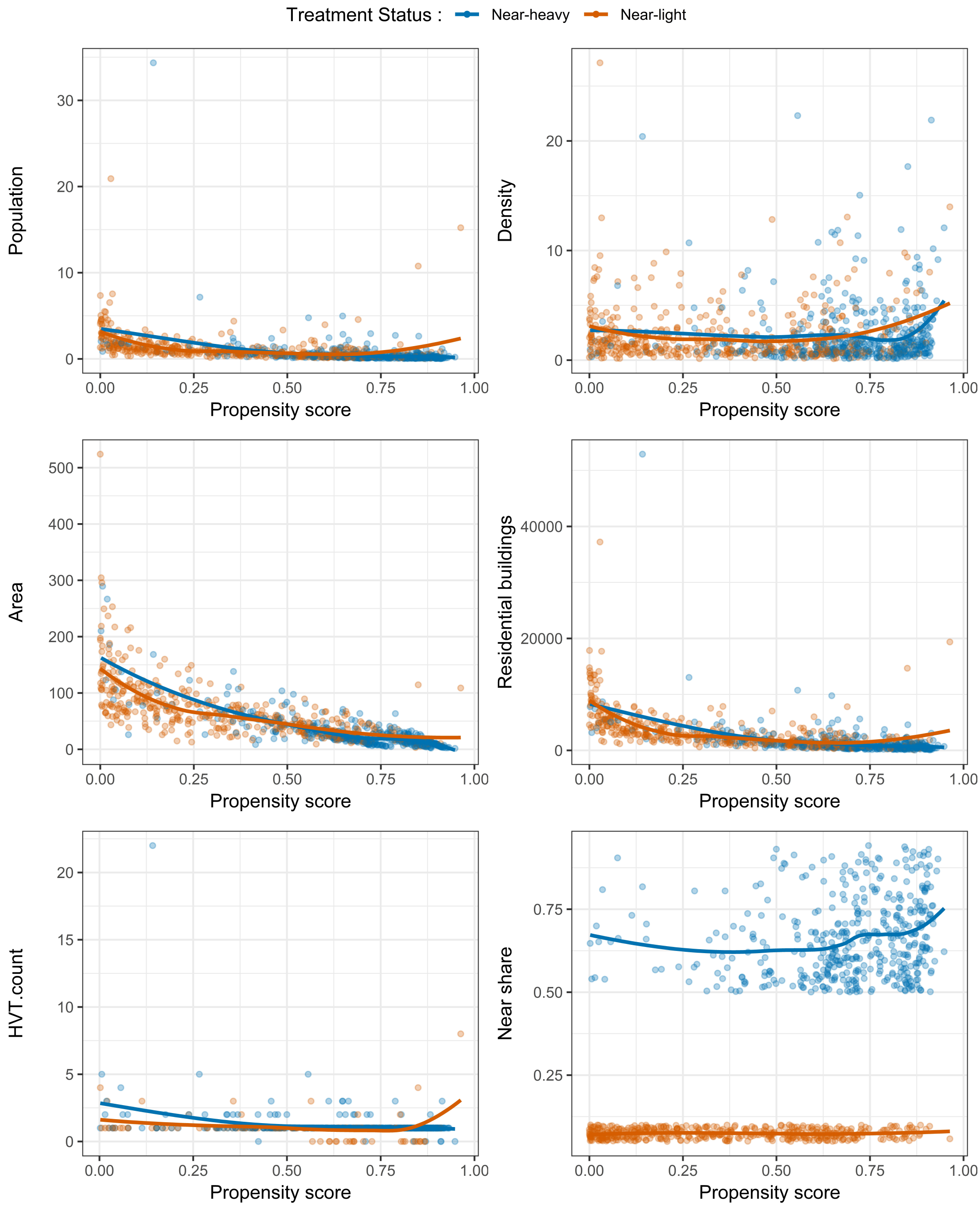
1.8 Appendix A

Figure A.1: Balance of matched municipalities by federal state



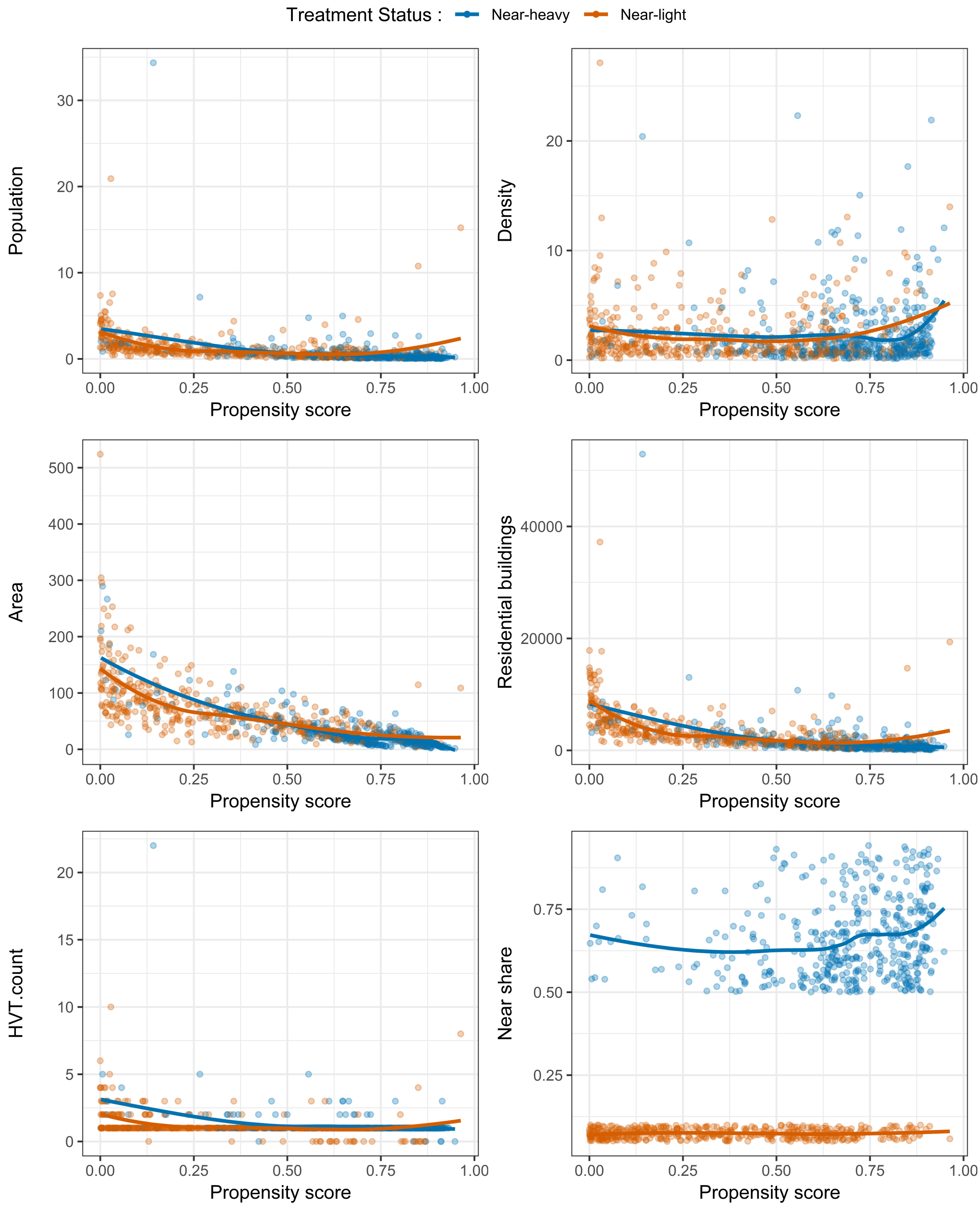
Notes: Municipalities are displayed with respect to their predicted FttP deployment probabilities. Colours refer to their status as either treatment or control group and to their actual deployment status. The scatter plots are sorted by federal state. The IDs correspond to these states in the following manner: 1 = Schleswig-Holstein, 3 = Lower Saxony, 4 = Bremen, 5 = North Rhine-Westphalia, 6 = Hesse, 7 = Rhineland-Palatinate, 8 = Baden-Württemberg, 9 = Bavaria, 10 = Saarland, 11 = Berlin, 12 = Brandenburg, 13 = Mecklenburg-Vorpommern, 14 = Saxony, 15 = Saxony-Anhalt, 16 = Thuringia. Hamburg (ID 2) experienced FttP expansion before 12/2013 and thus drops out of the set.

Figure A.2: Covariates of matched sample with replacement



Notes: Comparison of covariate values for treatment (*Near*-heavy in blue) and control (*Near*-light in orange) groups, when matching with replacement. For each of the four covariates used in the matching equation, the values for each municipality are displayed as points, with localities grouped by the tendencies of their *Near* shares. Additionally, a trend line for each group and covariate is provided. Propensity scores as well as the number of MDFs in a given municipality are also compared.

Figure A.3: Covariates of matched sample without replacement



Notes: Comparison of covariate values for treatment (*Near*-heavy in blue) and control (*Near*-light in orange) groups, when matching without replacement. For each of the four covariates used in the matching equation, the values for each municipality are displayed as points, with localities grouped by the tendencies of their *Near* shares. Additionally, a trend line for each group and covariate is provided. Propensity scores as well as the number of MDFs in a given municipality are also compared.

Table A.1: Median municipal characteristics by pre-existing FttP coverage

FttP.13> 0, ΔFttP > 0	Count	FttP.13	ΔFttP > 0	Population (in 10,000)	Density (in $100/km^2$)	HVT.count (abs.)
No, No	9916	0	0	0.16	0.9	0
No, Yes	956	0	0.064	0.21	1.15	0
Yes, No	8	0.865	0	0.01	0.36	0
Yes, Yes	303	0.125	0	0.62	2.34	1

Notes: Median characteristics for municipalities with and without FttP coverage in 2013 are displayed, separated in those that did (ΔFttP > 0) and did not receive expansion (ΔFttP $= 0$) during the observational period.

Table A.2: Determinants of FttP expansion at the extensive margin - by category and consolidated

Endogeneous Variable:	FttP.Exp [0,1]					
	T	Y	X	S	TYXS	TYXS.cons
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.17**	0.88***	0.22***	0.31***	0.75***	0.78***
	(0.06)	(0.13)	(0.06)	(0.02)	(0.14)	(0.13)
Vectoring.13.r	0.10				0.06	0.06
	(0.07)				(0.07)	(0.07)
Vectoring.13.n	0.28***				0.29***	0.29***
	(0.06)				(0.06)	(0.06)
HFC.13.r	−0.08*				−0.07·	−0.07·
	(0.03)				(0.03)	(0.03)
HFC.13.n	0.07*				0.07**	0.07**
	(0.03)				(0.03)	(0.03)
Δ Vectoring.r	0.07**				0.06**	0.06**
	(0.02)				(0.02)	(0.02)
Δ Vectoring.n	0.02				0.02	0.02
	(0.03)				(0.03)	(0.03)
Δ HFC.r	−0.04					
	(0.06)					
Δ HFC.n	0.02					
	(0.05)					
Vectoring.Exp.r	0.07					
	(0.06)					
Vectoring.Exp.n	0.02					
	(0.02)					
HFC.Exp.r	0.04·					
	(0.02)					
HFC.Exp.n	−0.02					
	(0.02)					
HVT.count	0.01***		−0.00		−0.01	−0.01
	(0.00)		(0.01)		(0.01)	(0.01)
Houses		0.00***			0.00	
		(0.00)			(0.00)	
Population		−0.02*			−0.00	0.01*
		(0.01)			(0.01)	(0.01)
Age		−0.01***			−0.01***	−0.01***
		(0.00)			(0.00)	(0.00)
Income p capita		0.00			0.00	
		(0.00)			(0.00)	
Density			0.01***		0.00	0.00
			(0.00)		(0.00)	(0.00)
1 Family Houses			0.03			
			(0.06)			
New Construction			0.90**		0.43	0.47
			(0.32)		(0.34)	(0.33)
Area			0.00***		0.00**	0.00***
			(0.00)		(0.00)	(0.00)
Forest Area			−0.00*		−0.00	
			(0.00)		(0.00)	
Industrial Area			0.01*		0.00	
			(0.01)		(0.01)	
Subsidies [0,1]				0.00·	−0.00	
				(0.00)	(0.00)	
Länder FE	YES	YES	YES	YES	YES	YES
R^2	0.09	0.08	0.07	0.06	0.10	0.10
Adj. R^2	0.08	0.07	0.07	0.05	0.09	0.09
Num. obs.	4011	4011	4011	4011	4011	4011

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: This table shows extensive margin regressions for each of the four characteristics classes T, Y, X and S - Technology (1), market size (2), accessibility (3) and subsidies (4), respectively; also shown is a combined specification of these characteristics in column (5). Column (6) shows the consolidated main specification used in the analysis. All specifications are estimated on the set of municipalities with both a *Near* area and no FttP deployment in 2013. For the combined specification, variables with too little variation or without relevance for the variable of interest were excluded to avoid variable inflation and issues with multicollinearity or convergence; though they were included in a robustness regression. For the consolidated specification, this procedure was repeated and other combinations tested using the combined one as basis.

Table A.3: Coefficient interpretation for the main extensive margin OLS specification

Variable	Δ	*Near* & *Remote*	*Remote*-only
Vectoring.13.r	10 pp	0.6 pp	1.8 pp
Vectoring.13.n	10 pp	2.9 pp	
Δ Vectoring.r	10 pp	0.6 pp	0.4 pp
Δ Vectoring.n	10 pp	-	
HFC.13.r	10 pp	-0.7 pp	-
HFC.13.n	10 pp	0.7 pp	-
Population	10.000	1 pp	-
Age	1 year	-1 pp	-1 pp
Density	$\frac{100 \text{ Inhabitants}}{km^2}$	-	-
New Construction	1 pp	-	0.5 pp
Area	10 km^2	0.5 pp	-
nearby10k	0/1	5 pp	9 pp
HFC.Exp.r	10 pp	-	0.4 pp

"pp": percentage point; "-": coefficient not significant;

" ": parameter not applicable to municipality

Notes: The table displays the interpretation for the estimated coefficients of the main extensive margin OLS regression (see Table 1.8). In column 2, the marginal increase per variable is noted in relevant units. In columns 3 and 4, resulting changes in the investment probabilities (Prob(FttP.Exp= 1)) are noted for the two municipality types (*Near & Remote*, *Remote*-only). Average investment probabilities are 10 percent for *Near* & *Remote* municipalities and 9 percent for *Remote*-only. The respective median values are at 8 and 5.

Table A.4: Average marginal effects for the main extensive margin Logit specification

Endogeneous Variable:	FttP.Exp [0,1]	
	Near & Remote	Remote-only
	(1)	(2)
(Intercept)	0.42^{**}	0.19^{*}
	(0.14)	(0.09)
Vectoring.13.r	0.08	0.15^{***}
	(0.06)	(0.03)
Vectoring.13.n	0.15^{**}	
	(0.05)	
Δ Vectoring.r	0.06^{*}	0.04^{*}
	(0.02)	(0.01)
Δ Vectoring.n	0.03	
	(0.02)	
HFC.13.r	$-0.06^{\cdot}$	-0.03
	(0.04)	(0.02)
HFC.13.n	0.07^{*}	
	(0.03)	
Population	0.00	0.02
	(0.00)	(0.03)
Age	-0.01^{***}	-0.01^{**}
	(0.00)	(0.00)
Density	0.00	-0.00
	(0.00)	(0.00)
New Construction	0.42	0.37^{*}
	(0.30)	(0.17)
Area	0.00^{***}	0.00
	(0.00)	(0.00)
HVT.count	-0.01	
	(0.01)	
nearby10k	0.04^{*}	0.06^{***}
	(0.02)	(0.01)
HFC.Exp.r		0.03^{**}
		(0.01)
Log Likelihood	-1154.21	-891.39
Deviance	2308.42	1782.78
Num. obs.	4011	3808

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: The table displays average marginal effects for the Logit models used in the main results displayed in Table 1.8. The first column shows results for municipalities with both *Near* and *Remote* areas, whereas the second column shows results for *Remote*-only municipalities. Coefficients and significances are similar to OLS results, thus affirming the decision to use OLS results and effect sizes in the main analysis as the linear specification is more robust.

Table A.5: Determinants of FttP expansion at the intensive margin - by category and consolidated

Endogeneous Variable:			Δ FttP			FttP.Exp. [0,1]
	T	Y	X	TYXS	TYXS.cons	TYXS.cons
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.55***	1.26***	0.57**	1.30**	1.52***	
	(0.04)	(0.36)	(0.19)	(0.44)	(0.37)	
Vectoring.13.r	0.28*			0.29*		0.06
	(0.13)			(0.14)		(0.07)
Vectoring.13.n	−0.08			−0.10		0.29***
	(0.11)			(0.11)		(0.06)
Δ Vectoring.r	−0.04			−0.05	−0.14**	0.06**
	(0.06)			(0.06)	(0.04)	(0.02)
Δ Vectoring.n	−0.12·			−0.10		0.02
	(0.06)			(0.07)		(0.03)
HFC.13.r	−0.11			−0.06		−0.07·
	(0.09)			(0.10)		(0.03)
HFC.13.n	−0.03			−0.04		0.07**
	(0.08)			(0.08)		(0.03)
Houses		−0.00**		0.00		
		(0.00)		(0.00)		
Population		0.02*		0.02·		0.01*
		(0.01)		(0.01)		(0.01)
Age		−0.01·		−0.01	−0.02*	−0.01***
		(0.01)		(0.01)	(0.01)	(0.00)
Income p capita		−0.00·		−0.00	−0.00·	
		(0.00)		(0.00)	(0.00)	
Density			−0.01*	−0.00	−0.01·	0.00
			(0.00)	(0.01)	(0.00)	(0.00)
1 Family Houses			−0.02	0.02		
			(0.22)	(0.23)		
New Construction			−1.08	−1.42·	−1.38·	0.47
			(0.74)	(0.77)	(0.77)	(0.33)
Area			−0.00·	−0.00	−0.00***	0.00***
			(0.00)	(0.00)	(0.00)	(0.00)
Forest Area			0.00	0.00		
			(0.00)	(0.00)		
Industrial Area			−0.01	−0.01		
			(0.02)	(0.02)		
HVT.count			0.00	−0.04*		−0.01
			(0.01)	(0.02)		(0.01)
Länder FE	YES	YES	YES	YES	YES	YES
R^2	0.34	0.31	0.31	0.37	0.35	0.10
Adj. R^2	0.30	0.28	0.27	0.32	0.32	0.09
Num. obs.	409	409	409	409	409	4011

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: This table shows intensive margin regressions for the three characteristics classes T, Y and X - technology (1), market size (2) and accessibility (3). Also shown is a combined specification of these characteristics in column (4). Column (5) shows the consolidated main specification used in the analysis, while column (6) is the extensive margin specification for comparison. The five intensive margin specifications are estimated by OLS on the set of municipalities with both a *Near* area and positive FttP deployment (FttP.Exp= 1).

Table A.6: Determinants of FttP expansion at the intensive margin - Heckman selection correction

Endogeneous Variable:	Δ FttP	
Municipality	N&R	R
(Intercept)	1.52^{***}	1.67^{***}
	(0.39)	(0.41)
Land.North	-0.09	-0.03
	(0.06)	(0.09)
Land.South	-0.28^{***}	-0.36^{***}
	(0.06)	(0.08)
Land.West	-0.24^{***}	-0.27^{**}
	(0.06)	(0.08)
Δ Vectoring.r	-0.22^{***}	-0.24^{***}
	(0.04)	(0.04)
Age	-0.01	$-0.02^{\cdot}$
	(0.01)	(0.01)
Income p capita	-0.00	0.00
	(0.00)	(0.00)
Density	-0.00	-0.03^{*}
	(0.00)	(0.01)
New Construction	-1.94^{*}	-0.83
	(0.80)	(0.69)
Area	-0.00^{***}	-0.01^{***}
	(0.00)	(0.00)
IMR1	-0.17^{***}	-0.16^{**}
	(0.04)	(0.06)
R^2	0.46	0.80
Adj. R^2	0.45	0.80
Num. obs.	409	346

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: This table shows the second stage - i.e. intensive margin - calculations for a two-stage heckman selection procedure. In the first stage, the extensive margins specification from Table 1.8 is used for a probit estimation on receiving investment. Under the assumption that this selection into investment does not depend on the change in coverage *given investment*, the intensive margin is calculated with the inverse Mills ratio (IMRI) bias correction. In contrast to the usual extensive and intensive margin specification of Table 1.8 and Table 1.9, the German federal states (*Länder*) are grouped into four categories. Since the number of municipalities with investment is very low for smaller federal states, using the *Länder* dummies is problematic. Some of the states drop out entirely, others are captured incompletely. The remaining states are sorted into groups of broadly similar characteristics and underlying trends: North, West, South and East; according to the structural divides in Germany.

Table A.7: Variable composition of the propensity score matching equation

	Cons.Match	XY.Match	MDF.match	MDFxXY.Match	Ext. Margin
(Intercept)	0.41***	0.31***	0.25***	0.26**	0.78***
	(0.01)	(0.09)	(0.01)	(0.09)	(0.13)
Population	0.03***	0.03***		0.01	0.01*
	(0.00)	(0.00)		(0.00)	(0.01)
Density	−0.00*	−0.00		−0.01***	0.00
	(0.00)	(0.00)		(0.00)	(0.00)
Area	−0.00***	−0.00***		−0.00***	0.00***
	(0.00)	(0.00)		(0.00)	(0.00)
Houses	−0.00***	−0.00***		−0.00***	
	(0.00)	(0.00)		(0.00)	
Age		0.00		−0.00	−0.01***
		(0.00)		(0.00)	(0.00)
Income p capita		−0.00		0.00	
		(0.00)		(0.00)	
1 Family Houses		0.09*		0.06·	
		(0.04)		(0.04)	
New Construction		−0.00		−0.03	0.47
		(0.20)		(0.19)	(0.33)
Forest Area		0.00		0.00	
		(0.00)		(0.00)	
Industrial Area		0.01**		0.01*	
		(0.00)		(0.00)	
HVT.count			−0.01**	0.03***	−0.01
			(0.00)	(0.01)	(0.01)
HVT.density.geo			1.53***	1.47***	
			(0.07)	(0.09)	
Vectoring.13.r					0.06
					(0.07)
Vectoring.13.n					0.29***
					(0.06)
Δ Vectoring.r					0.06**
					(0.02)
Δ Vectoring.n					0.02
					(0.03)
HFC.13.r					−0.07·
					(0.03)
HFC.13.n					0.07**
					(0.03)
Länder FE	YES	YES	YES	YES	YES
R^2	0.16	0.17	0.20	0.26	0.10
Adj. R^2	0.16	0.16	0.20	0.25	0.09
Num. obs.	4011	4011	4011	4011	4011

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: Comparison of propensity score matching equations (columns 1 to 4) in linear form. The logit results are qualitatively identical. Column 5 shows the best extensive margin equation to highlight similarities and differences between determinants for a high *Near* share and the probability of FttP deployment. Column 1 depicts the model used in the main analysis, whereas column 2 shows an expanded version including a broader range of market size and accessibility variables. In column 3, the *Near* shares are regressed on the number and geographical density of MDFs within a given municipality. This serves as a quality control for the model used since the MDF placements define the *Near* shares, but are themselves a consequence of infrastructure decisions made in the past century. In column 4, this control equation is expanded by including market size and accessibility variables from column 2. In comparison, the lack of explanatory power between the consolidated (1) and full market size/accessibility models (2) is negligible, while models including MDF information are more precise - as would be expected - but not exceedingly so.

Table A.8: Specification comparison: Matching set vs. main set on extensive and intensive margin

Endogeneous Variable:	FttP.Exp [0,1]		Δ FttP	
	(1)	(2)	(3)	(4)
(Intercept)	1.39***	0.78***	0.25	1.52***
	(0.23)	(0.13)	(0.93)	(0.37)
Vectoring.13.r	−0.12	0.06		
	(0.12)	(0.07)		
Vectoring.13.n	0.37***	0.29***		
	(0.11)	(0.06)		
Δ Vectoring.r	0.00	0.06**	−0.36*	−0.14**
	(0.04)	(0.02)	(0.14)	(0.04)
Δ Vectoring.n	−0.00	0.02		
	(0.05)	(0.03)		
HFC.13.r	−0.10	−0.07·		
	(0.06)	(0.03)		
HFC.13.n	0.11*	0.07**		
	(0.05)	(0.03)		
Population	0.03*	0.01*		
	(0.01)	(0.01)		
Age	−0.02***	−0.01***	0.02	−0.02*
	(0.00)	(0.00)	(0.02)	(0.01)
Density	0.00	0.00	0.02	−0.01·
	(0.01)	(0.00)	(0.01)	(0.00)
New Construction	0.08	0.47	2.21	−1.38·
	(0.56)	(0.33)	(2.48)	(0.77)
Area	0.00·	0.00***	−0.00·	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
HVT.count	−0.06**	−0.01		
	(0.02)	(0.01)		
Income p capita			−0.01·	−0.00·
			(0.01)	(0.00)
Länder FE	YES	YES	YES	YES
R^2	0.14	0.10	0.45	0.34
Adj. R^2	0.12	0.09	0.32	0.31
Num. obs.	990	4011	96	409

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: This table shows a comparison of the main extensive and intensive margin specifications between the set used in matching for the impact of Vectoring - (1) and (3) - and the complete set used in the main analysis - (2) and (4). For the extensive margin, linear specifications are used; the intensive margin is likewise an OLS model. In both comparisons, the signs of the coefficients remain the same. Effect sizes also differ little, though exceptions exist with regards to technology and new construction. Both can be attributed to the subset used in the matching procedure excluding larger municipalities, which possess - on average - more extensive legacy networks.

Table A.9: Determinants of FttP expansion at the intensive margin - Bavarian subset

Endogeneous Variable:	Δ FttP			
	Bavaria	Germany	Bavaria	Germany
	TYXS		TYXS.cons	
(Intercept)	1.55·	1.28**	1.90*	1.50***
	(0.88)	(0.44)	(0.83)	(0.37)
Vectoring.13.r	0.95***	0.28*		
	(0.24)	(0.14)		
Vectoring.13.n	−0.60*	−0.09		
	(0.25)	(0.11)		
Δ Vectoring.r	−0.01	−0.05	−0.02	−0.14**
	(0.10)	(0.06)	(0.08)	(0.04)
Δ Vectoring.n	−0.04	−0.10		
	(0.10)	(0.06)		
HFC.13.r	−0.13	−0.07		
	(0.15)	(0.10)		
HFC.13.n	0.02	−0.03		
	(0.11)	(0.08)		
Houses	−0.00·	0.00		
	(0.00)	(0.00)		
Population	0.29*	0.02·		
	(0.13)	(0.01)		
Age	−0.03	−0.01	−0.04*	−0.02*
	(0.02)	(0.01)	(0.02)	(0.01)
Income p capita	0.00	−0.00·	0.00	−0.00·
	(0.00)	(0.00)	(0.00)	(0.00)
Density	−0.00	−0.00	0.00	−0.01·
	(0.01)	(0.01)	(0.01)	(0.00)
1 Family Houses	−0.34	0.03		
	(0.33)	(0.23)		
New Construction	−1.73	−1.47·	−3.12	−1.44·
	(2.19)	(0.77)	(2.32)	(0.77)
Area	0.00	−0.00	−0.00	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
Forest Area	−0.00	0.00		
	(0.00)	(0.00)		
Industrial Area	−0.11	−0.01		
	(0.09)	(0.02)		
HVT.count	−0.02	−0.04*		
	(0.06)	(0.02)		
nearby10k	−0.04	−0.05	−0.04	−0.05
	(0.05)	(0.03)	(0.05)	(0.03)
Funding until 15	0.01		0.00	
	(0.01)		(0.01)	
Länder FE	NO	YES	NO	YES
R^2	0.40	0.38	0.10	0.35
Adj. R^2	0.19	0.33	-0.01	0.31
Num. obs.	74	409	74	409

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

Notes: This table compares the OLS intensive margins estimations between Bavaria (columns 1 and 3) and the whole of Germany, including Bavaria, in columns (2) and (4). Columns (1) and (2) use all available regressors, whereas columns (3) and (4) follow the consolidated specification used for the main results (see Table 1.9). The specifications consider only municipalities with *Near* & *Remote* areas. The Vectoring base coverage (Vectoring.13.r) and population are more important in Bavaria than in Germany as a whole, whereas nearly all other regressors lose significance. For the consolidated specification, the variables are jointly non-significant. Given the low number of observations, the apparent larger relevance of Vectoring and the general lack of FttP expansion in Bavaria, this not too surprising.

Table A.10: Variable list

Variable	Description	contained in:
Technology (T)		
FttP.13	FttP coverage in 2013	T
F2013	Dummy, whether FttP coverage was positive (1) by the end of 2013	T_E
FttP.17	FttP coverage in 2017	T
FttP.Exp	Dummy, whether FttP coverage changed (1) from 2013-17	Dep.var
Δ FttP	Change in FttP coverage from 2013-17	Dep.var
Vectoring.13.r	Vectoring coverage in 2013 in Remote area	T_E
Vectoring.13.n	Vectoring coverage in 2013 in Near area	T_E
Vectoring.Exp.r	Dummy, whether Vectoring coverage changed (1) from 2013-17 in Remote area	T_E
Vectoring.Exp.n	Dummy, whether Vectoring coverage changed (1) from 2013-17 in Near area	T_E
Δ Vectoring.r	Change in Vectoring coverage from 2013-17 in Remote area	T_E, T_I
Δ Vectoring.n	Change in Vectoring coverage from 2013-17 in Near area	T_E
HFC.13.r	HFC coverage in 2013 in Remote area	T_E
HFC.13.n	HFC coverage in 2013 in Near area	T_E
HFC.Exp.r	Dummy, whether HFC coverage changed (1) from 2013-17 in Remote area	T_E
HFC.Exp.n	Dummy, whether HFC coverage changed (1) from 2013-17 in Near area	T_E
Δ HFC.r	Change in HFC coverage from 2013-17 in Remote area	T_E
Δ HFC.n	Change in HFC coverage from 2013-17 in Near area	T_E
HVT.count	Amount of MDF in a municipality	T_E
HVT.dens.geo	Density of MDF based on Area (in MDF per km^2)	T
nearby10k	Dummy, whether a neighboring municipality within 10km is accessed with FttP (1) by the end of 2013	T_E
Market size (Y)		
Houses	Absolute number of residential houses	Y_E
Population	Absolute number of inhabitants (in 10.000)	Y_E
Age	Average age of a municipality's population (in years)	Y_E, Y_I
Income p capita	Average income per inhabitant (in 1.000 Euro)	Y_I
Accessibility (X)		
Density	Population density (in 100 inhabitants per km^2)	X_E, X_I
1 Family Houses	Quota of one-family residential houses of all residential houses	X_E
New Construction	Quota of newly built residential houses of all residential houses	X_E, X_I
Area	Area of a municipality (in 10 km^2)	X_E, X_I
Forest Area	Forest area of a municipality (in 1 km^2)	X_E
Industrial Area	Industrially used area of a municipality (in 1 km^2)	X_E
Subsidies (S)		
Subsidies	Dummy, whether a municipality received funding by either the federal or Bavarian program	S_E
Funding until 15	Accumulated subsidy payments received through the Bavarian program until 2015	S_E, S_I

Notes: This table summarizes all used variables for the estimations. Descriptions and unit of measurement are provided in the second column. The third column links the variable to the variable set it is contained in with respect to the main specifications. Column four lists all tables presenting estimations results in which the variable in question appears.

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Declaration of contribution

Hereby I, Niklas Michael Fourberg, declare that this chapter, entitled “Fiber vs. Vectoring: Limiting Technology Choices in Broadband Expansion” is co-authored with Alex Korff.

I have contributed substantially to the conception of the research project, the development of the empirical strategy, the analysis and graphical representation of the results, as well as the writing of the final manuscript.

Signature of the coauthor:

Alex Korff

Chapter 2

Monopoly Customization with Log-concave Consumer Preferences♠

Summary of the chapter

We analyze a monopolist's optimization problem of choosing the price and the degree of customization for a product. Consumer preferences are distributed according to a general log-concave density function over a horizontally differentiated characteristics space or time dimension. We show that the optimal customization choice may give rise to welfare inefficiencies depending on consumers' preference distribution. The model is fairly general and can be applied to various scenarios of products customized to personal preferences, including shopping hours, online content and infrastructure provision.

♠This chapter is co-authored with Tim Paul Thomes.

2.1 Introduction

Adapting products or services to consumer preferences has become an important entrepreneurial factor of success, not only to gain strategic advantage in competition, but also to access broader demand segments. Usually, consumer preferences exhibit different degrees of concentration and cannot generally be assumed to be uniform. For example, in the case of cultural goods, such as music and movies, there exist types that can be considered “mainstream”, while others are considered “independent”. The former targets preferences of a large consumer population, while the latter aims at niche segments with a less dense consumer concentration. This argument also applies to a pure geographical interpretation, where a more concentrated consumer distribution can be found in densely populated areas, or to opening hours of shops, where, for example, grocery purchases are preferably done in the early evening. Hence, in either case, non-uniform preference spaces can arguably be assumed to better fit reality than those relying on a purely uniform distribution. The purpose of this chapter is to address the question how products in such an environment can be optimally adapted to consumer preferences if consumer preferences are reflected by a general log-concave distribution function.[1]

The model relies on a spatial setting based on the seminal work of Hotelling (1929) and incorporates modifications of two critical features of his approach: Consumers are no longer uniformly distributed along a characteristics space and products are no longer solely interpreted as points in that characteristics space. Regarding the first modification, we allow for concentrated consumer preferences in that we assume the consumer density to be log-concave. Regarding the second, we consider products as intervals in the characteristics space that perfectly match not only a single, but a variety of preferences.

We focus on the case of a monopoly firm. This may be especially relevant when interpreting the product characteristics space in a purely geographical sense, where, e.g., essential facilities of network industries give rise to natural monopolies. Similarly, online retailing markets are dominated by firms with a high degree of market power.[2] Not only for this reason, but also to focus on potential inefficiencies that may arise in this setting, we restrict attention to the case of a single firm. We therefore look at a multidimensional optimization problem in spirit of Spence (1975), where the firm chooses the optimal customization with respect to the product characteristics in ad-

[1] The class of logarithmically concave distributions exhibit this feature very well (see Bagnoli and Bergstrom, 2005).

[2] For example, streaming content providers such as *Spotify* and *Netflix* preempt dominant positions in their markets. Similarly, *Amazon.com Inc.* obtained a market share of 37.5 percent in US online sales in the final two months of 2017 (see: https://www.digitalcommerce360.com/2018/01/11/amazons-e-commerce-market-share-dips-november-surges-december/).

dition to the optimal price.[3] However, our model differs from Spence (1975) in two aspects. First, we explicitly model consumer preferences that are non-uniformly distributed. Second, our approach, which builds upon a spatial product characteristics interpretation, involves the monopolist having to deal with two marginal consumers when the market is not fully served. Since our focus is on logarithmically concave consumer densities, our approach follows Caplin and Nalebuff (1991) in characterizing the monopoly equilibrium. We further derive conditions under which the customization of characteristics covered by the monopolist's product is chosen at a socially inefficient level. Employing a specific symmetric and non-uniform distribution function allows us to draw conclusions on how the size of this inefficiency is related to the shape of the consumer density: for more (less) concentrated preferences, the inefficiency tends to be large (small) for narrow product configurations and small (large) for wide ones.

To the best of our knowledge, this chapter is the first that studies the optimal provision of product attributes in terms of an interval-length product, thereby allowing for general log-concave consumer densities. What makes this approach appealing is that it provides a general setting covering a wide range of relevant applications, among which it may be used to address issues of concern, not only for scholars, but also for antitrust authorities. For example, as already mentioned above, one can interpret the characteristics space also as time dimension. Hence, the setting can be employed to obtain new findings on the optimal regulation of service hours under consideration of non-uniform consumer preferences with respect to time. Our results indicate that it should be taken into account that the concentration of preferences is crucial in determining socially efficient and desirable outcomes.

The remainder of the chapter is organized as follows. The next section discusses the relation to the existing literature. Section 2.3 sets up the model and develops the optimal monopoly price and interval product. Section 2.4 addresses the welfare implications and finally, Section 2.5 concludes.

2.2 Literature

The model has various applications among which (mass) customization of products and the regulation of shopping hours prominently made their way into the literature. We contribute to both because they naturally depart from the notion of a product representing a single attribute in a characteristics space. Moreover, either case can be expected to be characterized by consumer preferences that do not exhibit a uniform distribution.

First, we contribute to the literature on (mass) customization of consumer goods.

[3]We restrict attention to a uniform price. That is, we do not consider a monopolist that segments the market according to a price-variety schedule, as, for example, in Mussa and Rosen (1978).

Dewan *et al.* (2003) model customization as a firm's ability to choose multiple single attributes for one product in a characteristics space. They find that the scope of attributes may be smaller under duopolistic competition as compared to a monopoly. Similar to our approach, Alexandrov (2008) refers to customization as the possibility to offer an interval-length product that matches a variety of preferences. His framework is dealing with products being intervals in the Hotelling context. Bar-Isaac (2009) analyzes a competition scenario where the optimal horizontal product length is extended by a second vertical dimension. However, all of these approaches rely on uniformly distributed consumer preferences. In contrast, our model is fairly general by allowing for a wide class of log-concave density functions.

Second, we contribute to the literature on shopping hours. Shops choose a time interval during which their shops are open, where opening hours can also be interpreted as interval within a characteristics space of consumer preferences. For example, Inderst and Irmen (2005) examine price effects under the deregulation of shopping hours, where shops can open at day, night, never and always. Opening hours are therefore discrete and in addition, consumer preferences follow a piecewise uniform distribution. Shy and Stenbacka (2006) address the social optimality of business hours with continuous time intervals but assume prices to be exogenously given. Their approach incorporates non-uniform consumer preferences. However, these are reflected by a very specific linear triangular distribution function. Again, in contrast to all of these papers, our model provides a more general approach that allows not only for a wide range of non-uniformly logarithmically concave consumer densities, but also for endogenizing the pricing decision.

Finally, our model contributes to the literature strand dealing with log-concave consumer densities. Bagnoli and Bergstrom (2005) carefully review theorems on log-concave probability densities and their distribution functions and how they are used in various models. Caplin and Nalebuff (1991) establish existence and uniqueness of a price equilibrium in a setting of imperfect competiton with assumptions on the density functions being weaker than log-concavity. Building upon their model, Anderson *et al.* (1997) prove existence and uniqueness of an equilibrium in a successive location-then-price Hotelling-duopoly with general log-concave consumer densities. We contribute to this theory by looking at the case of a monopolist operating in a spatial setting characterized by a general log-concave consumer density. In contrast to e.g. Anderson *et al.* (1997), we deal with a scenario where the market may not be fully covered. In this setting, we prove existence and uniqueness of a monopoly equilibrium and draw general conclusions on how the monopoly outcome departs from the socially efficient outcome.

2.3 Model setup

We consider a single firm operating in a product characteristics space à la Hotelling (1929) of $[a, b]$, where $-\infty \leq a < b \leq \infty$. Apart from setting a price p the monopolist offers a configuration of its product that has a non-negative measure in the given characteristic space $[a, b]$. That is, products are not interpreted as single points but as an interval instead. This implies that all consumers within such an interval-long product obtain a good that perfectly matches their preferences and, therefore, they do not need to incur transportation costs.[4] Hence, in a monopoly equilibrium, the firm simultaneously sets the optimal (non-discriminatory) price p and the optimal location and length of its interval product $I = [x_L, x_R]$. The length of the product is denoted by Δ, which is determined by its endpoints x_L on the left side and x_R on the right side respectively, with $a \leq x_L < x_R \leq b$. Thus, the product length is $\Delta = x_R - x_L$.

Suppose that the development costs for the product are represented by the cost function $C(\Delta)$. We assume $C(\Delta)$ to be strictly increasing in Δ, that is, $C'(\Delta) > 0$. Since Δ is specified by the interval endpoints x_L and x_R, this implies that marginal costs of an increment in Δ are identical on either side of the interval. To satisfy second-order conditions, we require $C(\Delta)$ being sufficiently convex in Δ.[5]

Consumers are modeled as a continuum with mass normalized to unity. They buy at most one unit of the good and are distributed along $[a, b]$ according to the density function $f(x)$ which we specify below. Consumption provides a reservation utility of $R > 0$. Consumers pay a uniform price p for the product. If a consumer is located outside of the interval product and buys the product, she faces transportation costs of td with $d \geq 0$ representing the distance between that consumer's location and the interval endpoint closest to her.[6] A consumer being located within I gets her desired product configuration. Thus, the utility from consuming the good of a representative consumer located at x is

$$U(x) = \begin{cases} R - p & \text{if } x \in I \\ R - td(x) - p & \text{otherwise.} \end{cases} \tag{2.1}$$

Not consuming the good provides zero utility. Hence, there are two locations at which consumers are indifferent between buying the product or not, one on the left and one

[4]This setup follows closely the interpretation of Alexandrov (2008) and Bar-Isaac (2009) of firms offering a product in form of an interval along the Hotelling line.

[5]We provide the exact convexity condition in Proposition 1.

[6]This is either x_L or x_R depending on whether the consumer is located to the left or to the right of I. For example, if the consumer is located at a point x to the left of I and consumes the product, her transportation costs are $t(x_L - x)$. Note that we model consumers' transportation costs to be linear over the characteristics space for reasons of simplicity while we require the monopolist's cost to be convex in Δ. Although this seems counter-intuitive at first, the costs for the provision and consumption of additional characteristics can stem from fundamentally different processes in reality.

on the right side of the product interval. The locations of these indifferent consumers are given by

$$\widehat{x}_L = x_L - \frac{R-p}{t} \tag{2.2a}$$

to the left and

$$\widehat{x}_R = x_R + \frac{R-p}{t} \tag{2.2b}$$

to the right of the interval. Using (2.2a) and (2.2b) allows us to write down the monopolist's demand function, which is given by [7]

$$D(p, x_L, x_R) = \int_{\widehat{x}_L}^{\widehat{x}_R} f(x)dx = F(\widehat{x}_R) - F(\widehat{x}_L). \tag{2.3}$$

The consumer density function $f(x)$ with $f(x) > 0$, $\forall x \in [a, b]$ is assumed to be twice differentiable on the support $[a, b]$. Its cumulative distribution function is denoted by $F(x)$.

We perform the analysis under the following assumption:

Assumption 1. *The consumer density $f(x)$ is log-concave on $[a, b]$.*

The demand specification of $D = F(\widehat{x}_R) - F(\widehat{x}_L)$ is a cumulative distribution function drawn from $f(x)$. Log-concavity of $f(x)$ means that $\ln f(x)$ is concave in x, which requires that $\ln f(x)$ is twice continuously differentiable on $[a, b]$. The properties of $f(x)$ being log-concave are that the first derivative of $(\ln f(x))' = f'(x)/f(x)$ is a non-increasing function in x and that the second derivative is non-positive, i.e., $(\ln f(x))'' = f(x)f''(x) - f'(x)^2 \leq 0$.

Lemma 1. *If $f(x)$ is continuously differentiable and log-concave on $[a, b]$, then D is also log-concave on $[a, b]$.*

The proof of Lemma 1 allows us to formulate clear conditions under which the demand function is log-concave and follows the application of the Prékopa-Borell Theorem.[8] If the demand function is indeed log-concave, Caplin and Nalebuff (1991) generally showed that (under even weaker conditions) a firm's profit function is then quasi-concave in its price such that a solution to the monopolist's maximization problem with respect to the price always exists.

The proof of Lemma 1 is based on the following observations:

[7] In what follows, we referring to $D(\cdot)$ without its arguments.

[8] The Prékopa-Borell Theorem after Prékopa (1973) and Borell (1975) states that if a density function $f(\cdot)$ is log-concave, the corresponding cumulative distribution function $F(\cdot)$ is also log-concave.

Observation 1: $f(x)$ is log-concave if and only if $(\ln f(x))'' \leq 0$, that is, $f'(x)/f(x)$ is a non-increasing function of x on $[a, b]$.

Observation 2.a: Keeping $\widehat{x}_L$ constant, the demand function $D = F(\widehat{x}_R) - F(\widehat{x}_L)$ is increasing and log-concave in $\widehat{x}_R$ if $f'(\widehat{x}_R)D - f(\widehat{x}_R)^2 \leq 0$.

Observation 2.b: Keeping $\widehat{x}_R$ constant, $D = F(\widehat{x}_R) - F(\widehat{x}_L)$ is decreasing and log-concave in $\widehat{x}_L$ if $-f'(\widehat{x}_L)D - f(\widehat{x}_L)^2 \leq 0$.

From *Observation 1*, we get

$$\frac{f'(B)}{f(B)} \int_A^B f(t)dt \leq \int_A^B \frac{f'(t)}{f(t)} f(t)dt$$

for any $\{A, B\} \in [a, b]$, with $A < B$. Thus, regarding the indifferent consumers, which determine our demand function, it must necessarily hold that

$$\frac{f'(\widehat{x}_R)}{f(\widehat{x}_R)} \int_{\widehat{x}_L}^{\widehat{x}_R} f(t)dt \leq \int_{\widehat{x}_L}^{\widehat{x}_R} \frac{f'(t)}{f(t)} f(t)dt = f(\widehat{x}_R) - f(\widehat{x}_L) \leq \frac{f'(\widehat{x}_L)}{f(\widehat{x}_L)} \int_{\widehat{x}_L}^{\widehat{x}_R} f(t)dt \ . \quad (2.4)$$

From (2.4), we can therefore formulate two conditions referring to each indifferent consumer. For $\widehat{x}_R$, we have

$$f'(\widehat{x}_R)D - f(\widehat{x}_R)^2 \leq -f(\widehat{x}_R)f(\widehat{x}_L) \ . \quad (2.5)$$

Since $f(\widehat{x}_R) > 0$ and $f(\widehat{x}_L) > 0$, it is easily seen that if (2.5) holds, the condition in *Observation 2.a* is always satisfied. It follows that the demand is log-concave in $\widehat{x}_R$. Similarly, for $\widehat{x}_L$, log-concavity of $f(x)$ implies that

$$-f'(\widehat{x}_L)D - f(\widehat{x}_L)^2 \leq -f(\widehat{x}_R)f(\widehat{x}_L). \quad (2.6)$$

Again, if (2.6) holds, it follows that the condition in *Observation 2.b* is satisfied. Consequently, the demand is log-concave in $\widehat{x}_L$.[9]

2.3.1 Optimal pricing

Before analyzing the optimal product configuration, we determine the solution to the maximization problem of the monopolist with respect to the price. First, note that

[9] For further notes on the log-concavity of the demand specification, see Appendix B.1.

from (2.2a) and (2.2b), it follows that

$$\frac{\partial \widehat{x}_L}{\partial p} = 1/t > 0 \qquad \text{and} \tag{2.7a}$$

$$\frac{\partial \widehat{x}_R}{\partial p} = -1/t < 0. \tag{2.7b}$$

Hence, the demand function is a strictly diminishing function in the price, that is, $\partial D/\partial p = -(f(\widehat{x}_R) + f(\widehat{x}_L))/t < 0$.

The monopolist's maximization problem with respect to the price is

$$\arg \max_p \Pi_M(p, x_L, x_R) = pD - C(\Delta). \tag{2.8}$$

Lemma 2. *The monopolist's revenue function is quasi-concave in p. This holds independently of the choice of I.*

The proof of Lemma 2 follows Caplin and Nalebuff (1991). The details are provided in Appendix B.2.

The first-order condition with respect to p that solves (2.8) is given by

$$D + p\left(f(\widehat{x}_R)\frac{\partial \widehat{x}_R}{\partial p} - f(\widehat{x}_L)\frac{\partial \widehat{x}_L}{\partial p}\right) = 0. \tag{2.9}$$

Using (2.7a) and (2.7b) yields the optimal monopoly price that solves (2.9), which is given by

$$p^* = \frac{tD}{f(\widehat{x}_R) + f(\widehat{x}_L)}. \tag{2.10}$$

Hence, for any specific log-concave consumer density, the optimal price for a given x_L and x_R can already be stated from here.[10] Uniqueness of (2.10) follows from the above Lemma 2.

The monopolist's optimal price depends on the mass of indifferent consumers, which, in turn, are again implicitly determined by the price. Indeed, we cannot solve for the monopoly price explicitly, but we can characterize the unique monopoly equilibrium. Therefore, it is important to know how changes in I affect the equilibrium price. Using (2.7a), (2.7b), we have

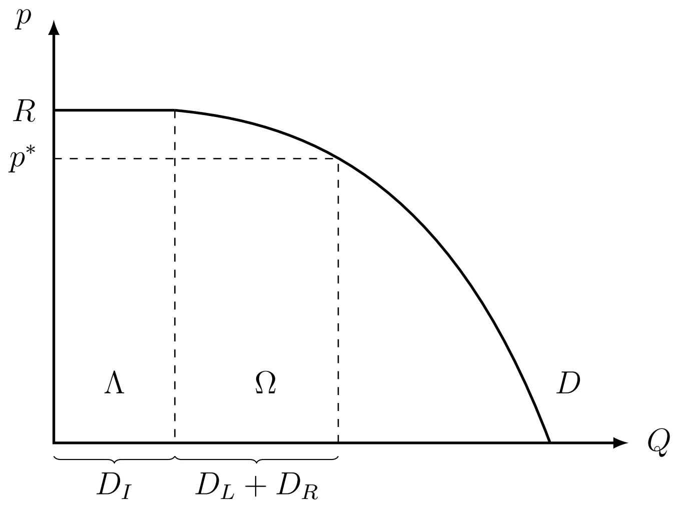
$$\frac{\partial p^*}{\partial x_L} = -\frac{t\left(f(\widehat{x}_L)^2 + f(\widehat{x}_L)f(\widehat{x}_R) + D \cdot f'(\widehat{x}_L)\right)}{D\left(f'(\widehat{x}_L) - f'(\widehat{x}_R)\right) + 2(f(\widehat{x}_R) + f(\widehat{x}_L))^2} \tag{2.11a}$$

$$\frac{\partial p^*}{\partial x_R} = \frac{t\left(f(\widehat{x}_R)^2 + f(\widehat{x}_L)f(\widehat{x}_R) - D \cdot f'(\widehat{x}_R)\right)}{D\left(f'(\widehat{x}_L) - f'(\widehat{x}_R)\right) + 2(f(\widehat{x}_R) + f(\widehat{x}_L))^2}\,. \tag{2.11b}$$

[10]Using (2.7a) and (2.7b), the elasticity of demand is $\eta = \frac{p}{[F(\widehat{x}_R)-F(\widehat{x}_L)]}\left(-\frac{1}{t}(f(\widehat{x}_R) + f(\widehat{x}_L))\right)$. Inserting p^* into η gives $\eta(p^*) = -1$, which is exactly the price elasticity at which the marginal revenue equals zero.

From (2.5) and (2.6) it follows that the numerator is strictly positive for both (2.11a) and (2.11b). This implies that $\partial p^*/\partial x_L < 0$ and $\partial p^*/\partial x_R > 0$. The intuition is straightforward and can be drawn from Figure 2.1.

Figure 2.1: Demand segments



The demand function is separable into three segments. The first covers all consumers within the product characteristics interval I. Let us denote this segment by D_I, which is $D_I = F(x_R) - F(x_L)$. The demand characterized by D_I is not sensitive to price changes in a sense that all consumers buy the respective product at any $p^* \leq R$. The second and the third segments are downward-sloping in p^* and consist of all consumers who incur transportation costs. Let us denote the segment to the left of x_L by $D_L = F(x_L) - F(\widehat{x}_L)$ and the segment to the right of x_R by $D_R = F(\widehat{x}_R) - F(x_R)$.[11] Thus, when increasing its price, the monopolist faces the trade-off between extracting a larger rent at the intensive margin (i.e., an increase in both rectangular areas Λ and Ω) and losing rent at the extensive margin (i.e., a decrease only in the rectangular area Ω) due to a decrease in $D_L + D_R$. Similarly, any increase in Δ and thus in D_I, which is brought about by an increase in x_R or a decrease in x_L respectively, increases the monopolist's rents from the consumers within D_I (that is, Λ increases) relatively to the rents appropriated from the consumers of $D_L + D_R$ (that is, Ω decreases). Thus, since an increasing price does not induce consumers within I to stop consuming the product, it becomes optimal for the monopolist to increase p^* as a response to an increase in Δ in order to maximize the aggregated areas Λ and Ω.

[11]Second order conditions with respect to the price are $\partial^2 D_R/\partial p^2 = f'(\widehat{x}_R)/t^2$ and $\partial^2 D_L/\partial p^2 = -f'(\widehat{x}_L)/t^2$. We show that the monopolist sets I so that $f'(\widehat{x}_L) > 0$ and $f'(\widehat{x}_R) < 0$. That is, D_L and D_R are decreasing and concave functions in p.

2.3.2 Optimal characteristics interval

Since we showed that the monopolist's profit function is always quasi-concave in the price (Appendix B.2), which allows to identify a unique price that evolves for any product specification, it remains to analyze the monopolist's optimal choice of the product characteristics interval. Since I is determined by its endpoints $[x_L, x_R] \in [a, b]$, with $x_L < x_R$, the monopolist needs to maximize its profit with respect to two dimensions on either side of the characteristics interval.[12] Given (2.10), the monopolist's maximization problem is

$$\arg\max_{x_L, x_R} \Pi_M(p^*, x_L, x_R) = p^*(x_L, x_R)\ D(x_L, x_R) - C(\Delta). \tag{2.12}$$

Taking the derivatives of (2.12) with respect to x_L and x_R yields

$$\frac{\partial p^*}{\partial x_L}\ D + p^* \frac{\partial D}{\partial x_L} = -C'(\Delta) \tag{2.13a}$$

for the left side of the characteristics interval and

$$\frac{\partial p^*}{\partial x_R}\ D + p^* \frac{\partial D}{\partial x_R} = C'(\Delta), \tag{2.13b}$$

for the right side of the characteristics interval, which can be expressed as follows:

$$\frac{\partial p^*}{\partial x_L}\ D + p^* \left[f(\widehat{x}_R) \frac{\partial \widehat{x}_R}{\partial p^*} \frac{\partial p^*}{\partial x_L} - f(\widehat{x}_L) \frac{\partial \widehat{x}_L}{\partial x_L} \right] = -C'(\Delta) \tag{2.14a}$$

and

$$\frac{\partial p^*}{\partial x_R}\ D + p^*\ \left[f(\widehat{x}_R) \frac{\partial \widehat{x}_R}{\partial x_R} - f(\widehat{x}_L) \frac{\partial \widehat{x}_L}{\partial p^*} \frac{\partial p^*}{\partial x_R} \right] = C'(\Delta). \tag{2.14b}$$

Note that increasing x_L narrows Δ, that is, $\partial\Delta/\partial x_L = -1$, while increasing x_R widens Δ, that is, $\partial\Delta/\partial x_R = 1$. Thus, the two first-order conditions (2.14a) and (2.14b) reflect the scenario of moving the interval product from the left to the right of the characteristic space. However, we are interested in the optimal length of the interval. Thus, in what follows, we interpret this such that x_L is moved to the left and x_R is moved to the right.

The two optimality conditions (2.14a) and (2.14b) say that the marginal revenue of incrementally moving one endpoint of the interval must equal the cost of that increment. To decompose all effects on marginal revenue from an increment in Δ in the

[12] Since our setting allows for non-uniform, and more specifically non-symmetric, consumer densities, the exact locations of the interval endpoints matter. Hence, we cannot maximize with respect to a general interval length Δ directly but have to treat each side separately.

simplest possible way, we reformulate (2.14a) and (2.14b) to a optimality condition of expanding the interval at side i in the form of

$$\frac{\partial p^*}{\partial \Delta} D + p^* \left[f(\widehat{x}_i) \left(1 - \frac{1}{t} \frac{\partial p^*}{\partial \Delta} \right) - f(\widehat{x}_{-i}) \frac{1}{t} \frac{\partial p^*}{\partial \Delta} \right] = C^{'}(\Delta) \,, \tag{2.15}$$

with $i \in \{L, R\}$. From (2.15), it can be seen that the marginal revenue associated with an increment in Δ is separable into a direct demand effect and an (indirect) price effect. Regarding the former, marginally expanding Δ implies that the demand of the consumers D_I within the characteristics interval increases similarly because one additional consumer type gets her desired product characteristic. This necessarily involves an outward-shift of the indifferent consumer $\widehat{x}_i$ by exactly the increment on the expanded side of the characteristics interval, resulting in a demand increase of $f(\widehat{x}_i)$. Regarding the second (indirect) price effect, we can reformulate (2.11a) and (2.11b) as follows

$$\frac{\partial p^*}{\partial \Delta} = \frac{t\,(f(\widehat{x}_i)^2 + f(\widehat{x}_{-i}) f(\widehat{x}_i) + D\,|f'(\widehat{x}_i)|)}{D\,(|f'(\widehat{x}_{-i})| + |f'(\widehat{x}_i)|) + 2(f(\widehat{x}_i) + f(\widehat{x}_{-i}))^2}, \tag{2.16}$$

which is strictly positive. This results in two opposing effects on the marginal revenue. First, a revenue increase over the set of inframarginal consumers of $(\partial p^*/\partial \Delta)D$. Second, the increase in the price causes a negative demand effect at the extensive margin that is of magnitude $|1/t\ (\partial p^*/\partial \Delta)|$ on either interval side. As a consequence, marginal revenue is impaired by $[1/t\ (\partial p^*/\partial \Delta)]\,(f(\widehat{x}_i) + f(\widehat{x}_{-i}))p^*$.

The generality of our model does not allow to obtain explicit solutions for the locations of endpoints and the interval length in the monopoly equilibrium. However, we can precisely characterize the monopolist's optimal choice. Substituting (2.10) and (2.16) into (2.15) yields that the optimality condition of expanding the interval at any side i with $i \in \{L, R\}$ boils down to

$$p^*(\widehat{x}_i, \widehat{x}_{-i}) f(\widehat{x}_i(p^*, x_i)) = C'(\Delta). \tag{2.17}$$

That is, at the monopoly equilibrium, the marginal revenue over the set of inframarginal consumers is just offset by the negative demand effect at the extensive margin. Hence, the monopolist chooses the optimal endpoints of I such that the marginal cost of an incremental increase in Δ equates the willingness to pay of the indifferent consumers on the side where the increment took place. Thus, the optimal interval endpoints x_L^* and x_R^* imply that the mass of indifferent consumers is identical at either side. Hence, we have that

$$f\left(\widehat{x}_L^*(p^*(x_L^*, x_R^*), x_L^*)\right) = f\left(\widehat{x}_R^*(p^*(x_L^*, x_R^*), x_R^*)\right) \equiv f(\widehat{x}^*), \tag{2.18}$$

characterizing all candidates for the optimal interval endpoints.
Given the above characterization, we can derive additional properties of the optimal interval product. First, log-concavity of $f(x)$ allows to determine the slope of the consumer density at $\widehat{x}_L^*$ and $\widehat{x}_R^*$. From that it follows that the demand interval centers around the mode M of the consumer density. More precisely, substituting (2.18) into the log-concavity conditions (2.6) and (2.5) yields that the following holds:

$$f'(\widehat{x}_L^*) \geq 0 \tag{2.19a}$$

$$f'(\widehat{x}_R^*) \leq 0 \; . \tag{2.19b}$$

Intuitively, the mode M is the product characteristic where the demand concentration is most dense. It is only natural that a monopolist chooses the product configuration such that consumers at M are always served. Whether M lies also within I or whether such consumers incur transportation costs instead, depends on how skewed $f(x)$ is. The characterization of the monopoly equilibrium is summarized in the following proposition.

Proposition 1. *Given the optimal pricing decision* (2.10)*, there exists a monopoly equilibrium involving unique interval endpoints x_L^* and x_R^*, that are set according to* (2.18)*, if*

$$\frac{tf(\widehat{x}^*)^3\left(f'(\widehat{x}_L^*) - f'(\widehat{x}_R^*)\right)}{4f(\widehat{x}^*)^2\left(f'(\widehat{x}_L^*) - f'(\widehat{x}_R^*)\right) - 2Df'(\widehat{x}_L^*)f'(\widehat{x}_R^*)} \leq C''(\Delta) \tag{2.20}$$

is satisfied.

The proof is provided in Appendix B.3. Existence requires that $C(\Delta)$ is sufficiently convex in Δ. The reason is as follows. Consider that $f(x)$ is so that consumer preferences are rather spread out, or that $f(x)$ is heavily skewed to one side. In that case, expanding the interval may involve constant (or even increasing) marginal returns. Thus, invoking (2.20) is needed to ensure an interior solution without imposing further restrictions on $f(x)$.

2.4 Social welfare

This section discusses the welfare implications of the model. Social welfare in this setting simply equals the aggregated rents of consumers and the monopolist. The consumer surplus is given by

$$\begin{aligned} CS = &\int_{\hat{x}_L}^{x_L} f(x)\left(R - p - t\left(x_L - x\right)\right)\,\mathrm{d}x + \int_{x_R}^{\hat{x}_R} f(x)\left(R - p - t\left(x - x_R\right)\right)\,\mathrm{d}x \\ &+ \left(F(x_R) - F(x_L)\right)\left(R - p\right) . \end{aligned} \tag{2.21}$$

Adding the monopolist's profit yields the social welfare function:

$$W = \int_{\widehat{x}_L}^{x_L} \left(R - t(x_L - x)\right) f(x)dx + \int_{x_R}^{\widehat{x}_R} \left(R - t(x - x_R)\right) f(x)dx \\ + R\left(F(x_R) - F(x_L)\right) - C(\Delta). \tag{2.22}$$

Our purpose is to restrict attention to the social optimality of I since the inefficiencies resulting from monopoly pricing follow the standard arguments. In our setting, prices are welfare neutral for consumers located within I. However, this is not the case for the demand segments D_L and D_R, where consumers do not obtain a perfect match of their preferences. For those consumers the price does not matter as transfer but rather influences the positions of $\widehat{x}_L$ and $\widehat{x}_R$ and with that the size of the demand segments D_L and D_R itself.

The welfare accumulated in these segments is represented by the first two terms of (2.22). Since price increments cause an inward shift of the positions of the indifferent consumers and thus a decrease in the demand, efficiency calls for the lowest possible price that satisfies the participation constraint of the monopolist with equality. This price maximizes the length of the segments D_L and D_R and thus aggregated surplus of consumers who are willing to take on transportation costs. Thus, the socially optimal price equals $C(\Delta)/D$ for a given Δ.

To determine efficiency of the product characteristics interval, social welfare is maximized with respect to the endpoints of the interval product x_L and x_R for any given pricing scheme. This can be the welfare maximizing pricing scheme outlined above or any other price. However, to focus solely on inefficiencies with respect to the interval length Δ, we assume in the following that the monopolist is not restricted in its pricing decision. Hence, we abstract from any potential price regulation scheme, so that it is set according to (2.10) solving the monopolist's maximization problem. Taking the derivative of W with respect to any of the two interval endpoints yields the optimality condition

$$\frac{\partial W}{\partial x_i} = \frac{\partial CS}{\partial x_i} + \frac{\partial \Pi_M}{\partial x_i} = 0, \text{ whith } i \in \{L, R\}\,. \tag{2.23}$$

Hence, the profit maximizing x_i^*, which solves $\partial \Pi_M / \partial x_i = 0$, only coincides with the efficient position x_i^W if it also provides a solution to $\partial CS / \partial x_i = 0$. As in the case of the optimality conditions of the monopolist, we need to maximize the consumer surplus with respect to both interval endpoints separately.

Consider therefore first that $i = R$. Differentiating (2.21) with respect to x_R yields

$$\frac{\partial CS}{\partial x_R} = \int_{x_R}^{\widehat{x}_R} \left(t - \frac{\partial p^*}{\partial x_R}\right) f(x)\mathrm{d}x - \int_{\widehat{x}_L}^{x_L} \frac{\partial p^*}{\partial x_R} f(x)\mathrm{d}x - \frac{\partial p^*}{\partial x_R}\left(F(x_R) - F(x_L)\right) \\ + f(\widehat{x}_R)\frac{\partial \widehat{x}_R}{\partial x_R}\left(R - p - t(\widehat{x}_R - x_R)\right) - f(\widehat{x}_L)\frac{\partial \widehat{x}_L}{\partial p^*}\frac{\partial p^*}{\partial x_R}\left(R - p^* - t(x_L - \widehat{x}_L)\right). \tag{2.24}$$

The second row of (2.24) represents the changes in the surplus of the indifferent consumers due to an increment in x_R. However, the indifferent consumers obtain zero utility by definition since their reservation utility minus their transportation costs equals the price. Thus, plugging (2.2a) and (2.2b) into both expressions of the second row of (2.24) shows that they simply turn to zero. Or to put it differently, consumers are indifferent since they realize zero utility from buying the product, irrespective of their location.
Thus, (2.24) can be expressed as

$$\frac{\partial CS}{\partial x_R} = D_R\left(t - \frac{\partial p^*}{\partial x_R}\right) - \frac{\partial p^*}{\partial x_R}\left(D_L + D_I\right) \ , \tag{2.25}$$

which boils down to

$$\frac{\partial CS}{\partial x_R} = tD_R - D\frac{\partial p^*}{\partial x_R} \ . \tag{2.26}$$

The first term on the right-hand side of (2.26) is the aggregated consumer gain from an increment in x_R, which is the aggregated reduction in transportation costs that is solely experienced by consumers to the right of x_R. The reason is that only they benefit from a product closer to their preference. The second term of (2.26) captures the respective aggregated consumer losses, resulting from an increase in the monopoly price that has to be borne by all consumers. Plugging (2.13b) and (2.26) into (2.23) yields that welfare is maximized with respect to x_R when

$$tD_R + p^*\frac{\partial D}{\partial x_R} = C^{'}(\Delta). \tag{2.27}$$

Comparing (2.27) with the solution to the monopolist's maximization problem, given by (2.13b), shows that both may differ. The monopolist extends the interval until the sum of its marginal revenue over inframarginal consumers and the indifferent consumers equals the marginal cost of an increment in Δ. In contrast, when maximizing social welfare, prices paid by the inframarginal consumers are ignored, since they are just transfers which are neutral in terms of total surplus. Thus, social welfare is maximized if the sum of the marginal savings in transportation costs (realized on the side of the increment) and the marginal surplus at the extensive margin (obtained by the monopolist) from an increment in Δ equates the marginal cost of the increment.

Hence, from the comparison of (2.27) and (2.13b), it follows that the monopolist sets x_R below the efficient level, i.e., the interval is set too narrow on the right side, if

$$\frac{tD_R}{D} > \frac{\partial p^*}{\partial x_R}, \tag{2.28}$$

that is, if $\partial CS/\partial x_R > 0$, while $\partial \Pi_M/\partial x_R = 0$. Applying the same procedure for the left endpoint of the characteristics interval shows that the monopolist sets x_L above the efficient level, i.e., the interval is set too narrow on the left side, if

$$\frac{tD_L}{D} > -\frac{\partial p^*}{\partial x_L} \,. \tag{2.29}$$

that is, if $\partial CS/\partial x_L < 0$, while $\partial \Pi_M/\partial x_L = 0$.

The distortion that may arise with respect to the interval endpoints follows the line of argument developed by Spence (1975) for the case of product quality. While the monopolist reacts to marginal consumers, the social planner is concerned about the average consumer. This discrepancy is also present in the present setting of provision of product characteristics. From (2.17), we know that the monopolist optimally expands the interval endpoints on either side until the willingness to pay of marginal consumers equals $C'(\Delta)$. Thus, $\partial p^*/\partial x_i$ represents the change in this willingness to pay of marginal consumers from an increment in Δ on side i which is relevant to the monopolist. Contrarily, the monopolist ignores the benefits to consumers that accrue due to a reduction in transportation costs. This reduction of size t is however only experienced by consumers on the side of the increment D_i. Thus, tD_i/D can be interpreted as the average marginal valuation from an increment in the interval length Δ. Hence, the monopolist underprovides in product characteristics, that is, the interval endpoints are set to narrow, if the willingness to pay of the marginal consumers exceeds the average marginal valuation from an additional increment in Δ. We summarize this finding in the following proposition.

Proposition 2. *From a social point of view, the monopolist needs to expand Δ on side $i \in \{L, R\}$ when*

$$\frac{tD_i}{D} > \frac{\partial p^*}{\partial \Delta} \,. \tag{2.30}$$

Although this result is in spirit similar to the finding of Spence (1975), it differs in the fact that the actual benefits of reduced transportation costs are experienced either by consumers of D_L or D_R and not the entire set of inframarginal consumers.[13]

2.4.1 Discussion of the results

Our model allows to formulate a condition when an inefficiency arises with respect to the optimal product interval, but generality of calculations makes it impossible to quantify the specific size of it. To gain some intuition, it is therefore helpful to introduce some simplifications. Consider therefore first that the underlying distribution is symmetric. In that case, the monopolist will center I symmetrically around the mode M such that we have an inversely identical slope of the density function at the indifferent consumers on either side, that is, $f'(\widehat{x}^*_L) = -f'(\widehat{x}^*_R) \equiv |f'(\widehat{x}^*)|$. This

[13]Note that if the firm had ability to price discriminate, consumers located in D_i that are closer to an interval-endpoint had to pay a higher price.

implies that the indifferent consumers are equidistantly located to the mode M. With a symmetric density, the previous underprovision condition (2.30) becomes

$$\frac{tD_i}{D} > t \cdot \frac{2f(\widehat{x}_i^*)^2 + D\,|f'(\widehat{x}^*)|}{8f(\widehat{x}_i^*)^2 + 2D\,|f'(\widehat{x}^*)|}, \text{ with } i \in \{L, R\}. \tag{2.31}$$

The higher the difference between the left and right hand-side expressions in (2.31), the higher is also the welfare optimizing adjustment starting from the monopolistic equilibrium. Hence, (2.31) not only provides information on when inefficiencies arise, but also on their magnitude. From this we can draw conclusions on how the existence and magnitude of the inefficiency in product characteristics depends on $|f'(\widehat{x}^*)|$, that is, the concentration of consumer preferences, or in other words, the concavity of the density function.

The degree of concentration mainly determines the monopolist's revenue from marginal consumers when expanding Δ. One can show that $\partial p^*/\partial\Delta$, that is, the right hand-side of (2.30), depends positively on $|f'(\widehat{x}^*)|$ such that for more concentrated distributions the valuation for product characteristics of marginal consumers is generally higher. The following illustration provides further intuition into this dynamic.

Imagine two arbitrary distribution functions of which the first $\tilde{f}(x)$ is rather concentrated, while the second $\dot{f}(x)$ is spread-out. With $\tilde{f}(x)$, the monopolist's revenue from marginal consumers ($D \cdot \partial p^*/\partial\Delta$) is therefore large for a small interval length Δ, but diminishes at a great rate when increasing Δ. The same is true for the mass of consumers $\tilde{D}_i$ who need to incur transportation costs. For a very small Δ, $\tilde{D}_i$ is large as the interval I is concentrated close to the mode of $\tilde{f}(x)$. As Δ increases, $\tilde{D}_i$ diminishes at a great rate and quickly moves to the flat tail of $\tilde{f}(x)$. This effect is amplified by a price effect, since an increasing Δ results in an increase in p^*, which moves the indifferent consumers closer to the interval endpoints. Hence, by increasing Δ both the amount of consumers who face transportation costs and the the distance over which they do so shrinks. This reduction is more severe if consumer preferences are rather concentrated. By contrast, in case of the spread-out density $\dot{f}(x)$, the revenue from marginal consumers and the mass of consumers who pay transportation costs are more even as Δ increases: as compared to $\tilde{f}(x)$ both are smaller if Δ centers closely around M and are larger for a wide interval length.

2.4.2 Illustration of the underprovision inefficiency

However, in our general setting, we can say only little about the mass of consumers who incur travel costs. In order to shape some intuition, assume in the following that the consumer price is a constant and given by $\bar{p}$. Fixing the price allows to abstain from price related feedback effects between the two interval sides. Thus, from (2.2a) and (2.2b), it follows that the distance between the indifferent consumers and the interval endpoint is always the same, irrespective of the density function.[14] Fixing the consumer price involves that changes in revenues from marginal consumers turn to zero ($D \cdot \partial p^*/\partial \Delta = 0$). The welfare optimizing adjustment, and with that the size of the inefficiency with respect to Δ, is therefore solely given by the numerator of the left hand-side of (2.30), that is, tD_i. Since this is always positive, the nature of the inefficiency is that of underprovision.

To illustrate how the size of the inefficiency depends on the concavity of the density function, we employ a logistic density function.[15] In what follows, assume that the consumer density function is given by

$$f(x) = \frac{e^{-\frac{x}{s}}}{s\left(e^{-\frac{x}{s}} + 1\right)^2} \, . \tag{2.32}$$

This density function is symmetric and has its mode (median) at zero, that is, $M = 0$. The shape parameter $s > 0$ in our setting provides a measure for the concentration of preferences around M. As discussed above, let us employ comparative statics by comparing two density functions that differ in their degree of the concentration of consumer preferences. Denote therefore (again) by $\tilde{f}(x)$ a concentrated density function, where we set $\tilde{s} = .2$ and by $\dot{f}(x)$ a spread-out density function, where we set $\dot{s} = 1.3$.

Since both densities are symmetric, the inefficiency is identical on each side of the interval. Thus, we measure the single-side inefficiency as non-considered profits by the monopolist due to a underprovision in Δ as follows

$$\Phi \equiv t \int_{\widehat{x}_L}^{x_L} f(x)\, \mathrm{d}x \equiv t \int_{x_R}^{\widehat{x}_R} f(x)\, \mathrm{d}x, \tag{2.33}$$

where $f(x)$ is given by (2.32). Under rather concentrated preferences, i.e., $\tilde{f}$ with $\tilde{s} = .2$, the monopolist can cover a relatively large mass of consumers with a small Δ. However, given that the interval endpoints are set sufficiently close to M, the mass of consumers who take on transport costs is similarly large and so is the resulting inefficiency $\tilde{\Phi}$.[16] However, $\tilde{\Phi}$ decreases quickly when increasing Δ since the mass of consumers (both at the position of the indifferent consumer and the interval endpoint) falls rapidly when moving towards the tails of the distribution. The opposite applies for the inefficiency $\dot{\Phi}$ that arises in case of the dispersed preference distribution with $\dot{f}$ and $\dot{s} = 1.3$. For a small Δ, the mass of consumers centered around M is relatively

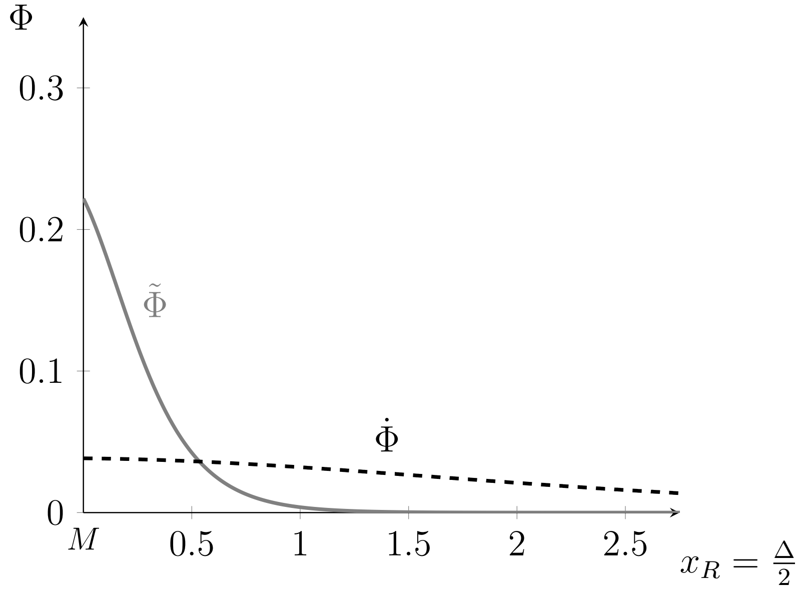
[14] Note that with a fix price, convexity of the cost function is no longer needed to obtain an interior solution for the maximization problem of the monopolist and the social welfare. Log-concavity of the density function ensures strictly diminishing marginal revenues and social benefits.

[15] The logistic distribution exhibits a log-concave probability density function over the (unbounded) support of $[-\infty, \infty]$. Note that many other distributions exhibit log-concave probability density functions, which would serve our purposes as they satisfy conditions (2.5) and (2.6). Examples include uniform, normal, exponential, extreme value, Gamma, Weibull, Chi-squared, and Beta distributions.

[16] We refer to the inefficiency as $\tilde{\Phi}$ under $\tilde{f}$ and as $\dot{\Phi}$ under $\dot{f}$.

small and so is $\dot{\Phi}$. If the interval endpoints are shifted outwards (and Δ increases), the mass of consumers at the positions of the indifferent consumers and the interval endpoint diminish only slowly. Thus, $\dot{\Phi}$ remains relatively large, also at high values for Δ. The scenario is illustrated in Figure 2.2, where, for the sake of exposition, we restrict attention to the right interval bound. It shows how the size of the inefficiency varies with a given interval endpoint under the two density functions $\tilde{f}$ and $\dot{f}$.

Figure 2.2: Inefficiency: tight vs. spread out preferences



Notes: The figure displays the inefficiencies for the parameters of $R = 1$, $\bar{p} = .8$ and $t = .8$.

To gain even deeper intuition to what extent Δ is chosen too small in the monopoly equilibrium we further stylize the above example. From the optimality conditions for the social welfare (2.27) and for the monopolist (2.13b), we know that the optimal interval endpoints are determined by the marginal cost of an increment in Δ, that is, by $C'(\Delta)$. Assume therefore a simple convex quadratic cost function given by $C(\Delta) = \Delta^2$, so that $C'(\Delta) = 2\Delta$.[17] Now we can numerically analyze how the interval endpoints which maximize social welfare differ to the monopolist's choice. Assume again the concentrated density of $\tilde{f}$ with $\tilde{s} = .2$ and further that $R = 1$, $\bar{p} = .8$ and $t = .8$ (analogously to Figure 2.2).[18] Using the logistic density function specified by (2.32) and the respective optimality conditions (2.27) and (2.13b), we obtain that the monopolist chooses its optimal interval endpoints so that $\Delta^* \approx .2363$, while social welfare is maximized if the interval endpoints are such that $\Delta^W \approx .2938$. Integrating $\tilde{f}$

[17] Since $\Delta = x_R - x_L$ and $f(x)$ is given by (2.32), any marginal increment in Δ on either side causes costs of $C'(\Delta) = 4x_i$, with $i \in \{L, R\}$.

[18] Note that this implies that the distance between the interval endpoints and the positions of the indifferent consumer always equals .25 independent of the density function.

from $\widehat{x}_R^*$ to $\widehat{x}_R^W$ while accounting for the symmetric other interval side, yields that the mass of consumers served in the monopoly equilibrium is too small by approximately 0.0322. Thus, in our stylized scenario, roughly three percent of all consumers are not served by the monopolist although they should be served in the socially efficient regime. The associated total inefficiency due to underprovision of product characteristics is then $2\tilde{\Phi} \approx .3512$.

2.5 Conclusion

This chapter analyzes a firm's choice of a consumer price and the configuration of a customized interval-length product that covers a variety of attributes for general log-concave consumer densities. We characterize the monopoly equilibrium and prove existence of both a unique price and a unique interval representing the degree of customization. The product interval is optimally set so that consumers with the most common preference are always served and buy the product.

We show that in a monopoly equilibrium, not only the price, but also the length of the interval may depart from the social optimum. We find that the interval is set too narrow if the average (marginal) valuation of an increment in the interval length exceeds the marginal valuation of the respective indifferent consumers. The distortion is rooted in the fact that the monopolist focuses solely on marginal consumers while ignoring the benefits of reduced transportation costs to consumers who do not obtain their ideal product configuration. Using a specific (symmetric and non-uniform) consumer density function, we find that a high inefficiency tends to arise if consumer preferences are rather concentrated and the interval product is narrow, while the opposite applies to a wide interval. In contrast, dispersed consumer preferences tend to involve an inefficiency that remains rather constant in the length of the product interval. Our model can be applied to a variety of scenarios, including any markets where products are customized to consumer preferences and shopping hours. It allows to draw conclusions on optimal pricing and product configurations as well as possible inefficiencies for a wide range of general (log-concave) consumer densities. Moreover, in contrast to the existing literature, it deals with the realistic scenario of a market being not fully covered in a setting of spatial product differentiation.

2.6 Appendix B

B.1 Notes on the log-concavity of demand

The demand specification of $D = F(\widehat{x}_R) - F(\widehat{x}_L)$ is determined by the two indifferent consumers. As a consequence, a change in one indifferent consumer may also have an indirect (opposite) effect on the other indifferent consumer. In our setting, such an effect is induced through the equilibrium price of (2.10). Consider for example that the price increases due to a change in $\widehat{x}_R$. From (2.2a) and (2.2b), it follows that the demand then shrinks since $\widehat{x}_L$ increases while $\widehat{x}_R$ decreases. However, such effects are not critical to the property of log-concavity of D.

To show this, let us look at the indifferent consumer on the right side. Allowing for a simultaneous change of $\widehat{x}_L$, the demand function is then log-concave in $\widehat{x}_R$ if $[f(\widehat{x}_R) - f(\widehat{x}_L)(\partial\widehat{x}_L/\partial\widehat{x}_R)]/D$ is non-increasing in $\widehat{x}_R$.

Again, given that (2.5) is satisfied, this always holds. The reason is that if $f(x)$ is log-concave on the support $[a, b]$, it must necessarily be also log-concave on any subinterval of this support. Since $f'(x)/f(x)$ is non-increasing in x on $[a, b]$, thereby satisfying (2.5) and (2.6), any demand configuration with $a \leq \widehat{x}_L < \widehat{x}_R \leq b$ must consequently be log-concave in the positions of the indifferent consumers.

B.2 Existence of an optimal price

Quasi-concavity in p of a monopolist's revenue function ensures existence of a price optimum. Caplin and Nalebuff (1991) provide a sufficient condition for this quasi-concavity of the revenue function in p: D^{-1} must be convex in p.

D^{-1} is convex in p if $\partial^2 D^{-1}/\partial p^2 \geq 0$. In our case, by using (2.7a) and (2.7b), this holds if

$$2(f(\widehat{x}_R) + f(\widehat{x}_L))^2 + D(f'(\widehat{x}_L) - f'(\widehat{x}_R)) \geq 0\ . \tag{B.1}$$

Condition (B.1) is equivalent to

$$\begin{aligned}&2f(\widehat{x}_R)^2 + 2f(\widehat{x}_R)f(\widehat{x}_L) - f'(\widehat{x}_R)D + \\ &2f(\widehat{x}_L)^2 + 2f(\widehat{x}_R)f(\widehat{x}_L) + f'(\widehat{x}_L)D \geq 0\ .\end{aligned} \tag{B.2}$$

It follows that the first (upper) term of (B.2) is strictly positive by virtue of (2.5), while the second (lower) term of (B.2) is strictly positive by virtue of (2.6). Thus, log-concavity of the consumer density on $[a, b]$ ensures quasi-concavity of the monopolist's revenue function in the price.

B.3 Proof of Proposition 1

In principle, the optimality condition for the monopolist is satisfied if the marginal revenue of expanding the interval length Δ equals its marginal cost, as indicated by (2.15). While the log-concavity of $f(x)$ secures the existence of an unique optimal price, we still have to show that the solutions x_L^* and x_R^* to the systems of FOCs (2.14a) and (2.14b) indeed constitute a global maximum. For this purpose the sufficient condition requires the Hessian to be negative semi-definite. The Hessian is given by

$$H_M(x_L, x_R) = \begin{bmatrix} \frac{\partial^2 \Pi_M}{\partial x_L^2} & \frac{\partial^2 \Pi_M}{\partial x_L \partial x_R} \\ \frac{\partial^2 \Pi_M}{\partial x_R \partial x_L} & \frac{\partial^2 \Pi_M}{\partial x_R^2} \end{bmatrix} \tag{B.3}$$

where the interior of the square brackets can be derived to be

$$\begin{bmatrix} -f(\widehat{x}_L)\frac{\partial p^*}{\partial x_L} - f'(\widehat{x}_L)\left(1 + \frac{1}{t}\frac{\partial p^*}{\partial x_L}\right)p^* - C''(\Delta) & -\frac{\partial p^*}{\partial x_R}\left(f'(\widehat{x}_L)\left(\frac{p^*}{t}\right) + f(\widehat{x}_L)\right) + C''(\Delta) \\ \frac{\partial p^*}{\partial x_L}\left(-f'(\widehat{x}_R)\left(\frac{p^*}{t}\right) + f(\widehat{x}_R)\right) + C''(\Delta) & f(\widehat{x}_R)\frac{\partial p^*}{\partial x_R} + f'(\widehat{x}_R)\left(1 - \frac{1}{t}\frac{\partial p^*}{\partial x_R}\right)p^* - C''(\Delta) \end{bmatrix}.$$

Let us first explain the second derivatives of the cost function. It follows from our assumption that $C(\Delta)$ is twice continuously differentiable that the cross-partial derivatives are symmetric. Thus, since $\Delta = x_R - x_L$, the cross-partial derivatives satisfy

$$\frac{\partial^2 C(\Delta)}{\partial x_L \partial x_R} = \frac{\partial^2 C(\Delta)}{\partial x_R \partial x_L} = \frac{\partial^2 C(\Delta)}{\partial \Delta^2}\frac{\partial \Delta}{\partial x_L}\frac{\partial \Delta}{\partial x_R} = -C''(\Delta)\,. \tag{B.4a}$$

Similarly, the second-partial derivatives can be expressed as follows:

$$\frac{\partial^2 C(\Delta)}{\partial x_L^2} = \frac{\partial^2 C(\Delta)}{\partial \Delta^2}\left(\frac{\partial \Delta}{\partial x_L}\right)^2 = C''(\Delta) \tag{B.4b}$$

$$\frac{\partial^2 C(\Delta)}{\partial x_R^2} = \frac{\partial^2 C(\Delta)}{\partial \Delta^2}\left(\frac{\partial \Delta}{\partial x_R}\right)^2 = C''(\Delta)\,. \tag{B.4c}$$

The above expressions greatly simplify the calculation of the determinant and the analysis of the definiteness of the Hessian.

First, negative semi-definiteness of $H_M(x_L, x_R)$ requires that the first leading principal minor is non-positive, that is, $\partial^2 \Pi_M / \partial x_L^2 \leq 0$. Inserting p^* given by (2.10) and $\partial p^* / \partial x_L$ as obtained in equation (2.11a) into $\partial^2 \Pi_M / \partial x_L^2$ and using the equilibrium characteristic (2.18) of the optimal endpoints x_L^* and x_R^* yields that the first leading principal minor is non-positive if

$$\frac{t\left(D^2 f'(\widehat{x}_L^*)f'(\widehat{x}_R^*) - 4Df'(\widehat{x}_L^*)f(\widehat{x}^*)^2 + 4f(\widehat{x}^*)^4\right)}{2f(\widehat{x}^*)\left(D\left(f'(\widehat{x}_L^*) - f'(\widehat{x}_R^*)\right) + 8f(\widehat{x}^*)^2\right)} \leq C''(\Delta) \tag{B.5}$$

holds.

Second, the determinant of the Hessian needs to be non-negative, that is

$$\frac{\partial^2 \Pi_M}{\partial x_L^2}\frac{\partial^2 \Pi_M}{\partial x_R^2} - \left(\frac{\partial^2 \Pi_M}{\partial x_L \partial x_R}\frac{\partial^2 \Pi_M}{\partial x_R \partial x_L}\right) \geq 0.$$

Again, using the equation for the optimal price (2.10) and making use of the equilibrium characteristic (2.18) for the monopolist's choice of the interval endpoints, the above equation can be expressed as follows:

$$\frac{tf(\widehat{x}^*)^3\left(f'(\widehat{x}_L^*) - f'(\widehat{x}_R^*)\right)}{4f(\widehat{x}^*)^2\left(f'(\widehat{x}_L^*) - f'(\widehat{x}_R^*)\right) - 2Df'(\widehat{x}_L^*)f'(\widehat{x}_R^*)} \leq C''(\Delta). \tag{B.6}$$

The convexity assumption on $C(\Delta)$ implies that $C''(\Delta) > 0$. Subtracting (B.5) from (B.6) yields

$$\frac{tD\left(f'(\widehat{x}_L^*)f'(\widehat{x}_R^*)D - f(\widehat{x}^*)^2\left(3f'(\widehat{x}_L^*) - f'(\widehat{x}_R^*)\right)\right)^2}{2f(\widehat{x}^*)\left(2f(\widehat{x}^*)^2\left(f'(\widehat{x}_L^*) - f'(\widehat{x}_R^*)\right) - f'(\widehat{x}_L^*)f'(\widehat{x}_R^*)D\right)\left(D\left(f'(\widehat{x}_L^*) - f'(\widehat{x}_R^*)\right) + 8f(\widehat{x}^*)^2\right)}.$$

The numerator is always positive and the denominator is positive given the equilibrium characteristic of $f'(\widehat{x}_L^*) \geq 0$ and $f'(\widehat{x}_R^*) \leq 0$, which directly follows from log-concavity of $f(x)$. Thus, (B.6) imposes a stronger restriction on $C''(\Delta)$ than (B.5). Consequently, a monopoly equilibrium with unique interval endpoints exists if (B.6) is satisfied.

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Declaration of contribution

Hereby I, Niklas Michael Fourberg, declare that this chapter, entitled "Monopoly Customization with Log-concave Consumer Preferences" is co-authored with Tim Paul Thomes.

I have contributed substantially to the conception of the research project, the development of the theoretical model, the analysis and graphical representation of the results, as well as the writing of the final manuscript.

Signature of the coauthor:

Tim Paul Thomes

Chapter 3

Let's Lock them in: Collusion under Consumer Switching Costs

Summary of the chapter

Consumer switching costs decrease the price elasticity of existing consumers while increasing competition for new consumers. This chapter studies the effect of this twofold pricing incentive on firms' behavior in a 2x2 factorial design experiment both with present and absent switching costs and with and without the ability to communicate. I find that consumer switching costs reduce the price level towards new consumers but do not affect price levels for existing consumers. Markets with switching costs are overall less tacitly collusive which translates into higher incentives to collude explicitly. The results have implications for antitrust policy.

3.1 Introduction

Switching costs affect firms' price incentives in a twofold manner. Consumers for whom it is costly to switch are less price elastic and are therefore targeted by higher prices. On the other hand, this prospect facilitates competition for consumers who have not bought yet and creates a downward pressure on prices that may compensate consumers in advance. This state dependent pricing pattern is often referred to as "invest-and-harvest" behavior whose composite effect on prices is seen as ambiguous (Klemperer, 1995).

Firms' market power over locked-in consumers and the potential for consumer harm also depends on the "investment" intensity, that is, the level of competition prior to consumers' lock-in (Farrell and Klemperer, 2007). It is increasingly important to account for this state dependency in form of locked-in and new consumers if firms can indeed price discriminate between the two groups. Neglecting this can lead to an erroneous attribution of high "harvesting" prices to tacit collusion when firms are in fact acting non-cooperatively (Che *et al.*, 2007). In addition to this, theoretical studies of Padilla (1995) and Anderson *et al.* (2004) find countervailing effects of switching costs' size on the sustainability of collusion. Hence, it is increasingly difficult to infer the competitiveness of a market, let alone tacit or explicit collusive outcomes, from observed prices.

This chapter studies the effect of consumer switching costs on firms' price setting behavior in a laboratory experiment under the presence and absence of firms' ability to communicate. I compare levels and distributions of prices in a 2x2 experiment design and assess the twofold pricing incentive's effect on the degree of tacit collusion and firms' incentive to collude explicitly. Firms engage in repeated duopolistic Bertrand competition with homogeneous goods, an environment which is seen as favorable for tacit collusive agreements in the literature (Dufwenberg and Gneezy, 2000) and by the European Commission (Davies *et al.*, 2011).

The experimental design consists of two periods and captures two distinct characteristics. First, consumers live only for a finite time, meaning they retire from the market after the second period. Second, firms are able to price discriminate, that is, they can distinguish between consumers who already bought the product and those who did not, but not between own and rival's customers.[1] This framework is especially suited to pursue the research aim for one main reason: It ensures the observability of firms' "invest-and-harvest" motive. This would vanish if consumers were indistinguishable and firms set a somewhat consolidated price targeted at both consumer groups.[2]

[1] Gehrig *et al.* (2011) analyze the effects of this history-based price discrimination due to switching costs on market entry.

[2] The model abstracts from any other source of product heterogeneity as this would only weaken the identification of switching costs' effect on prices. Costs of switching a supplier after an initial purchase

Furthermore, consumers with a two-period lifetime are admittedly creating end-game effects but ensure that "invest-and-harvest" incentives occur separately in different periods. In the case of longer living consumers (three periods or more), there is at least one period in which prices could be driven by both motives simultaneously.[3] Hence, it is especially consumers' two-period lifetime that ensures the separate observability of firms' pricing incentives.[4]

There is a strong case to study the effect of consumer switching costs on tacit and explicit collusion in a laboratory environment. The experimenter has complete control over subjects' ability to communicate which allows for a distinct analysis of these market outcomes, something economic theory does not incorporate.[5] Further, empirical studies on cartels are based only on detected cartels which may differ in key characteristics from undetected ones (Posner, 1970). Due to this sample-selection, empirical findings on cartels are not generally valid but only applicable to this subset. Laboratory experiments, however, can overcome this since all market participants are observed independent of detection which is a clear advantage when assessing collusive environments.

This study contributes to the literature on the competitiveness of markets under consumer switching costs and is the first, to the best of my knowledge, to investigate the effect of firms' "invest-and-harvest" incentives in a laboratory environment.

The analysis provides four main results. First, consumer switching costs lead to lower price levels towards new consumers, compared to a zero switching cost market, perfectly resembling firms' "investment" behavior. Price levels targeted at existing customers are not affected. The second result is that communication facilitates coordination on higher prices which is in line with findings of Fonseca and Normann (2012) and Cooper and Kühn (2014) who both show that free-form communication is an effective coordination device in dilemma games. If firms are communicating, switching costs have no effect. Thus, communication helps firms to overcome the switching cost

make goods ex-post heterogeneous. A second source of heterogeneity would induce an incentive to increase prices that counteracts the investment and supplements the harvesting incentive. Thus, abstracting from heterogeneous products is the cleaner design choice.

[3]Suppose consumers live for three periods and switching costs occur after the initial purchase in the first period. In such a scenario prices in the second period could be either driven by motives of "harvesting" existing customers or again "investing" to gain a higher market share since there is a third period of competition. This is especially unfavorable in the experimental implementation as observed prices cannot perfectly be accounted to either of these motives.

[4]Markets that are characterized by the properties above are for instance reduced software licenses that are distributed at a discounted price to students or other groups. Once the status as a student voids, a consumer naturally buys a license of a full version only once. This setting translates to any market with finitely living or participating, identifiable consumers in which firms' incentives resemble the "invest-and-harvest" motive. Further examples are age related products like baby or infant products such as toys and diapers. But also banking services, consulting services and other durable goods and their aftermarkets exhibit these features.

[5]On a related topic see Gehrig and Stenbacka (2007) for firms that are not communicating but share customer information under switching costs.

induced "investment" pressure. Third, switching costs induce distributional effects. Compared to a situation with zero switching costs, prices towards new consumers are more concentrated at marginal cost level. Furthermore, the price distribution of firms who manage to serve all new consumers exhibits a lower variance towards existing customers. Those firms "harvest" their customer base through prices in close proximity to the static Nash equilibrium. The fourth result is that switching costs dampen the scope for tacit collusion as supra-competitive profits are reduced compared to a market without switching costs. On the other hand, profit gains from communication are more pronounced making explicit conspiracies more attractive.

The concept of consumer switching costs and their associated effects have been extensively studied in the theoretical literature. Despite the success of models that include a finite time horizon and identifiable consumer groups (see Klemperer, 1995, 1987b), they often fail to give an unambiguous intuition on the overall competitiveness of those markets. Therefore, many studies withdraw from this binary state dependency and turn to infinite time horizon frameworks to particularly avoid end-game effects and provide predictions for a market steady state (see Beggs and Klemperer, 1992; Padilla, 1995; Dubé *et al.*, 2009). Beggs and Klemperer (1992) investigate duopolistic competition under constant consumer entry and exit in every period. They find that markets are less competitive if switching costs are large enough such that consumers are perfectly locked-in with their initial suppliers. Padilla (1995) relaxes this restrictive assumption but nevertheless finds a relaxing effect on competition. However, a more recent approach of Dubé *et al.* (2009) challenges this view and shows a negative effect of consumer switching costs on equilibrium prices and profits while also allowing for imperfect lock-in. In their empirically calibrated model the "investment" incentive dominates the "harvesting" motive mirroring in spirit our first main result. Intuitively, firms want to "invest" in market share as well as prevent own customers from switching which together outweigh the "harvesting" incentive in their framework. Hence, the overall competitive effect of consumer switching costs remains ambiguous independent of the model's time horizon.

The remainder of the chapter is structured as follows. Section 3.2 introduces the experimental model and develops relevant equilibria on which we base our hypotheses that are formulated in Section 3.3. The following Section 3.4 then outlines the design of the conducted experiment whose treatment effects are analyzed in Section 3.5. Finally, Section 3.6 concludes.

3.2 The Model

The experimental switching cost model is based on the theoretic framework by Klemperer (1995, Section 3.2). It incorporates a finite time horizon in form of two subsequent market stages ($k = 1, 2$) in which switching costs emerge only in the second stage, representing the "mature" market. Firms engage in duopolistic Bertrand competition for market shares and do not discount profits from the second stage.

We denote p_k^i as firm i's chosen price in market stage k and $\pi_k^i(p_k^i, p_k^j)$ as the corresponding profit in that given market stage.[6] Goods are produced at constant marginal cost of c in both stages. Consumer mass is of size m and exhibits inelastic unit demand of one up to a reservation price of $p^{max} \geq c$. After their initial purchase in $k = 1$ consumers face switching costs of S in case they switch suppliers in $k = 2$.

The remainder of this section first analyses the strategic one-shot interaction under positive consumer switching costs, the case of absent switching costs and then discusses the infinitely repeated competition cases.

3.2.1 Positive switching costs

I consider positive switching costs that are not too large such that consumers are only imperfectly locked-in. This feature is important in order to preserve firms' pricing incentives in $k = 2$, in the sense that a firm can still induce consumer switching if it chooses to price aggressively (see Padilla, 1995; Dubé *et al.*, 2009). We therefore impose the following assumption.

Assumption 1. *We assume consumer switching costs to be positive and of intermediate size such that* $\frac{p^{max}-c}{4} \leq S \leq \frac{p^{max}-c}{2}$.

Consumers are myopic and maximize their single market stage utility.[7] Hence, they buy whatever product is cheapest, also taking into account potential costs of switching. If consumers are indifferent, their demand is split up equally among the two firms. Firm i's profit function is displayed in Appendix C.1.

We can identify three distinct subgames for $k = 2$. Two of previous monopolization, by the rival or by firm i, and one subgame in which firms shared market demand equally beforehand. Since we solve for subgame perfect Nash equilibria we start the analysis with the different subgames in $k = 2$.

Monopolization

Given that a firm i was able to monopolize the market in $k = 1$, it will either keep its market share, lose one half of it, or lose it entirely in $k = 2$. We can formulate equilibrium prices and profits as follows.

[6] Note that $\pi_k^i(p_k^i, p_k^j)$ is a step function and not continuously differentiable in firms' prices.

[7] See also Klemperer (1987a) for a discussion of switching costs under different levels of consumer expectations and future tastes.

Proposition 1. *Let $p_1^i < p_1^j$. Then, in the subgame perfect Nash equilibrium, a firm i also monopolizes the market in $k = 2$ under prices of*

$$p_2^{i^{MI}} = p_2^j + S = c + S; \quad p_2^{j^{MI}} = c\,, \tag{3.1}$$

and profits of

$$\pi_2^{i^{MI}} = S \cdot m\,; \;\; \pi_2^{j^{MI}} = 0. \tag{3.2}$$

Proof. See Appendix C.2.[8] □

Intuitively, a firm i who previously served the entire market demand will set a price (just below) $p_2^i = p_2^j + S$ that maximally exploits its own customer base while ensuring not to lose any market share to its rival. Given this pricing strategy, any rival's price of $p_2^j > c$ implies a profitable deviation for firm j as it can attract at least some demand if it lowers its price.

Equal split

If firms set identical prices in $k = 1$, they are endowed with a symmetric customer base entering competition in $k = 2$. As a consequence, they face a trade-off between harvesting their existing customer base with a price of (just below) $p_2^i = p_2^j + S$ or undercut a rival's price with (just below) $p_2^i = p_2^j - S$.[9] We find an equilibrium in mixed strategies of the following form.

Proposition 2. *Let $p_1^i = p_1^j$. Then, in the subgame perfect Nash equilibrium, a firm i randomizes in $k = 2$ over two disjoint price sets of*

$$p_2^{i^S} \in \mathbf{A} \dot\cup \mathbf{H}\,, \tag{3.3}$$

with

$$\mathbf{A} = \left[\frac{p^{max} + 2S + c}{2} - S, p^{max} - S\right] \equiv [\underline{\alpha}, \bar{\alpha}]$$
$$\mathbf{H} = \left[\frac{p^{max} + 2S + c}{2}, p^{max}\right] \equiv [\underline{\epsilon}, \bar{\epsilon}]$$

and earns expected profits of

$$E\left[\pi_2^{i^S}\right] = \left(\underline{\epsilon} - c\right)\frac{m}{2} > \pi_2^{i^{MI}}\,. \tag{3.4}$$

Proof. See Appendix C.2. □

[8] This is the price equilibrium also shown in Klemperer (1987b, Section 2) and Farrell and Klemperer (2007, Section 2.3.1).

[9] As Farrell and Klemperer (2007, Footnote 31) put it, this setting "generally eliminates the possibility of pure-strategy equilibria if S is not too large".

The set of **A** contains aggressive prices a firm i would charge in order to win over the rival's customer base, whereas harvesting prices are part of the set **H**. This mixed pricing equilibrium is in spirit similar to findings of Padilla (1992), Fisher and Wilson (1995) and Shilony (1977) who all find mixed strategy equilibria in single-staged settings with switching costs (or equivalent components). Note from (3.4) that firm i's expected equilibrium profits in the split subgame exceed those from i's monopolization subgame. The symmetric distribution of market shares induces both firms to compete less fiercely for the rival's customer base. Firms' behavior can be interpreted in terms of two "fat cats" in the sense of Farrell and Shapiro (1988) who do not compete for rival's imperfectly locked-in consumers but rather "harvest" existing ones. Asymmetric market shares under a monopolization, on the contrary, work as a commitment for the outsider to price aggressively.

Market stage one & equilibria

Firms maximize combined profits ($\Pi^i = \pi_1^i + \pi_2^i$) from both market stages. Obviously, a firm i does not want to overprice its competitor in $k = 1$, since this implies zero profits in either market stage. Monopolization in $k = 1$ is always profitable from a single period perspective, but it consequences lower profits in the following subgame of $k = 2$ relative to an equal split. Given a rival's price, the trade-off between monopolization and splitting market demand gives rise to the following equilibria.

Proposition 3. *There exist multiple, symmetric, Pareto-rankable subgame perfect Nash equilibria in pure strategies that include first stage prices over the interval of*

$$p_1^i = p_1^j \in \left[2c - \underline{\epsilon}\,;\ \underline{\epsilon} - 2S\right]. \tag{3.5}$$

Firms realize total equilibrium profits of

$$\Pi^{i^*} = \Pi^{j^*} \in \left[0, 2\left(\underline{\epsilon} - c - S\right)\frac{m}{2}\right]. \tag{3.6}$$

Proof. See Appendix C.2. □

Firm i finds it only optimal to monopolize if it can do so at a relatively high price, that lies above the interval stated in (3.5). In this case monopolization profits in $k = 1$ are substantial and make up for fiercer competition in the subsequent subgame. However, this is naturally not feasible in equilibrium as the rival could profitably deviate. These equilibria are in line with results of Suleymanova and Wey (2011) who also find a market sharing equilibrium in Bertrand competition under switching costs.

3.2.2 Absent switching costs

If switching costs are zero ($S = 0$), the equilibria developed in Section 3.2.1 are not simply applicable since switching costs of size zero fall outside the interval from **Assumption 1**. If switching a supplier is costless in $k = 2$, the game condenses to two identical market stages of symmetric Bertrand competition. Most important to note is that the price decision in $k = 2$ is completely history independent since the market outcome in $k = 1$ is irrelevant. Firms cannot form customer bases because switching costs simply do not emerge. Consequently, there is only one kind of subgame in $k = 2$ which is identical to that of $k = 1$.

As a result, firm i will play the classic Bertrand equilibrium price in each market stage ($p^i_B = c$) and shares the market demand twice. A firm i's combined equilibrium profits from both market stages are then naturally

$$\Pi^{i*}_B = 2\,(c - c)\,\frac{m}{2} = 0\ . \tag{3.7}$$

3.2.3 Dynamic competition

Under infinitely repeated interaction any higher price can be sustained in equilibrium compared to the respective one-shot interactions if agents are sufficiently patient. Naturally, among those the reservation price p^{max} maximizes joint payoffs. Hence, collusive firms will set

$$p^{i^C}_1 = p^{i^C}_2 = p^{i^C}_B = p^{max} \tag{3.8}$$

under positive as well as absent switching costs.

Given that firms employ a Nash reversion grim trigger strategy as a punishment, the sustainability of collusion in the repeated game differs in two dimensions. First, the static game with positive switching costs already exhibits multiple Nash equilibria in pure strategies. Therefore, a firm i has the opportunity to employ either of these as a competitive threat as part of the punishment scheme. Firms can either punish *harshly* in setting the lowest equilibrium price of $p^i_1 = 2c - \underline{\epsilon}$ or more *smoothly* in granting positive competitive profits. However, firms just punish with $p^i_B = c$ if switching costs are zero. Second, the two market stages within a playing period enable firms to deviate either in $k = 1$ or $k = 2$.

Given **Assumption 1**, a deviation in $k = 1$ is always preferable to a deviation in $k = 2$ if switching costs are present. This is driven by two effects. First, a deviator in $k = 1$ monopolizes the market and will still earn positive profits of size $S \cdot m$ in the subsequent subgame in $k = 2$. Second, if a firm deviates in $k = 2$ instead, it has to do so by the amount of S to compensate consumers and induce consumer switching. Both effects make the deviation in $k = 1$ more attractive. This dynamic resembles exactly the "invest-and-harvest" incentives of the static game. Although a deviator is already punished with static equilibrium play, she still captures positive profits in the second market phase ($k = 2$) because she "invested" in a high market share through her defection. Obviously, if firms are patient enough, they can overcome the pressure to "invest-and-harvest" and sustain collusion.

Contrarily, under absent switching costs firms rather deviate in the second market stage of competition. Table C.5 in Appendix C.5 provides further information on the critical discount factors for every timing-punishment intensity pair which ensures p^{max} to be the symmetric collusive equilibrium price.

We define $\delta_G^{i^{I,k}}$ as firm i's critical discount factor in scenario $G \in \{SC, B\}$ (positive or absent switching costs) under the rival's punishment intensity $I \in \{H, S\}$ (*harsh* or *smooth*) when considering a deviation in market phase k. Naturally, a *smooth* punishment increases the required discount factor whereas punishing *harshly* makes a deviation more costly and collusion more sustainable. Accounting for **Assumption 1** one can then show that

$$\delta_{SC}^{i^{H,1}} \leq \delta_B^{i^2} = \frac{1}{3} \leq \delta_{SC}^{i^{S,1}} \tag{3.9}$$

holds. It is therefore ambiguous whether switching costs increase or decrease the sustainability of collusion, since the direction of the effect depends on the punishment scheme and thus the chosen equilibrium price of the static game. Both directions are within the scope of the model.

For the specific experiment parameters the highest discount factor required to secure the existence of collusive equilibria is $\delta_{SC}^{i^{S,1}} = \frac{2}{5}$. If subjects perceive the experiment's continuation probability of $\frac{7}{8}$ in fact as a discount factor, coordination on every price of the spectrum is an equilibrium outcome of the repeated game. Dal Bó (2005) and Fréchette and Yuksel (2017) find for repeated dilemma games that the continuation probability has indeed an effect on subjects' play.

3.3 Hypotheses

Building upon the model, firms should, according to the Nash prediction, collude on p^{max} in any treatment since interactions take place repeatedly and the implemented continuation probability is sufficiently high. This would consequently imply that we cannot expect any treatment effects neither from switching costs nor communication. However, we find this highly unlikely and numerous literature findings provide evidence for communication's positive effect on collusion in dilemma games (Fonseca and Normann, 2012; Cooper and Kühn, 2014). We rather conjecture that the static equilibrium solutions are better predictions for subjects' play if communication is impossible and formulate the following hypotheses:

Hypothesis 1. *Without communication, switching costs will decrease the price level in the first market stage ("investment") and lead to an increased price level in the second market stage ("harvest").*

Based on the literature mentioned above we expect that free-form communication serves also in our experimental setting as an effective coordination device.

Hypothesis 2. *Price levels will be higher if firms are able to communicate compared to treatments without communication.*

Since it is already difficult to infer the competitiveness of switching cost markets from only the price level, we are also interested in how switching costs affect other moments of the price distribution than just mean prices. In addition to this, there is also a conjecture in the literature that switching costs could provide focal points in the pricing space which would break the market into defined submarkets. This would make tacit market sharing outcomes easier to implement (Klemperer, 1987b; Farrell and Klemperer, 2007). Hence, it could be promising to investigate the effect of switching costs on the price distribution but we are unaware of an experimental study that already did this. We therefore cannot justify a testable hypothesis here but rather formulate:

Exploratory Research Question 3. *How do switching costs affect the price distribution?*

One main focus of the paper is to provide evidence on the effect of switching costs on the degree of tacit collusion and the incentives to collude explicitly. As Ivaldi *et al.* (2003, p.5) put it, "...tacit collusion is a market conduct that enables firms to obtain supra-normal profits, where 'normal' profits corresponds to the equilibrium situation...". Therefore, we measure supra-competitive profits, that is, the intensity of tacit collusion, as the amount of profits that exceeds the static Nash equilibrium level.

Building upon this, a realistic way to measure a firm's incentive to collude explicitly is the profit it would gain through such an agreement compared to colluding only tacitly.[10] However, we cannot derive a testable hypothesis on either of those profit measures. Even if Hypotheses 1 and 2 hold, it is unclear whether the "invest" or "harvest" motive dominates and how these relate to overall profits and supra-competitive profits. The same applies to profit gains from communication as it is unclear how the

[10] In reality a firm's decision to collude explicitly comes also at some costs. Not only potential fines in case of detection but also opportunity costs in rejecting the option to collude tacitly. Hence, the monetary gains which can be realized through colluding explicitly should be the decisive factor in this decision and are also of interest in our analysis. See also Fonseca and Normann (2012) who elaborate more comprehensively on this.

profit difference between the talk and no-talk treatments is affected by switching costs. We therefore formulate:

Exploratory Research Question 4. *How do switching costs affect firms' supra-competitive profits and profit gains from communication?*

3.4 Experimental design

To test the formulated hypotheses the experiment implementation is designed to closely follow the underlying model. The parameters are chosen to satisfy the condition of **Assumption 1**. Experimental markets consist of $m = 30$ consumers that buy one product up to a reservation price of $p^{max} = 100$. The symmetric duopolists face constant marginal cost of production of $c = 40$. A firm is able to single-handedly serve all consumers in the market. Firms choose prices simultaneously and independently from the nearly continuous action set $p_k^i \in \{0, .., 100\}$.[11]

The 2x2 design consists of four treatments in total. In N20 (No communication with Switching Costs) and T20 (Talk with Switching Costs) switching costs are of size $S = 20$. Whereas in N0 and T0 they are of size $S = 0$. Subjects are able to communicate in treatments T20 and T0.

Table 3.1: Treatment overview

	$S = 20$	$S = 0$
Disabled communication	**N20**	**N0**
Enabled communication	**T20**	**T0**

A playing period consists of one iteration of the static game and is played repeatedly. Subjects played a total of three supergames and participated only in one treatment. They were randomly re-matched to a stranger between each supergame. This between-subjects design is especially robust against anticipated learning effects. Subjects play more repetitions of the same treatment while the treatment comparisons separately by supergame account for supergame specific effects. The length of a supergame was determined by a random termination rule, proposed by Roth and Murnighan (1978), for which Fréchette and Yuksel (2017) show that it induces the highest cooperation rates compared to other termination methods in repeated prisoners' dilemma interac-

[11] In practice the price set cannot be fully continuous for the reason that the experimental software allows only for a finite number of decimal places, in this case eight. We are allowing subjects to use all of them when choosing their price to keep the experimental implementation as close as possible to the theoretical framework.

tions. The incorporated continuation probability was 0.875.[12] Supergame lengths were determined ex-ante and were constant over all treatments. The first supergame lasted for 6 playing periods, the second for 12 periods and the third for 5 periods.

In T20 and T0 subjects were able to communicate for a duration of 120 seconds prior to each supergame via an instant-messenger tool. There was no communication during supergames such that we can perfectly abstract from renegotiation effects. The time limit was sufficiently long to communicate experiment relevant information and subjects were allowed to post as many messages they liked during that time span. Hence, communication was in free-form which is seen as one of the least restrictive and therefore most effective in facilitating coordination in dilemma games (see Crawford, 1998; Brosig *et al.*, 2003). Subjects were aware that they communicated only with their rival and not other participants.

Each treatment was conducted in a separate session with 24 participants. Instructions were handed out in written form and subjects answered additional control questions on their computer screen prior to the experiment. Price and text inputs were made via a computer terminal and feedback was given after each market stage on current own and rival's prices, own profits and the resulting consumers' purchasing decision.[13] Additionally, subjects had information on their own accumulated profits but not on their rival's. Furthermore, the user interface included a profit calculator which was accessible in all treatments.

Sessions were programmed in z-Tree (Fischbacher, 2007) and were run at the DICE Lab at the Heinrich-Heine University Düsseldorf in which a total of 96 students participated. Subjects were awarded with a show-up fee of €4 and earned an "Experimental Currency Unit" called "Taler" with an exchange rate of 3,000 Taler : €1. Subjects were payed their cumulative earnings from all supergames. Potential losses were offset against the show-up fee and average payment was €16.03 and session duration reached from 50 up to 70 minutes.

3.5 Treatment effects

This section reports quantitative results on the effect of switching costs and communication on prices, profits and the competitiveness of markets. The conducted tests are all non-parametric and consider subjects' posted prices. Test statistics are computed separately over supergames and are based on market level data.[14]

[12]The continuation probability of 0.875 ensures that coordination on any price is a collusive equilibrium of the repeated game if firms punish according to a Nash reversion trigger. See Section 3.2.3.

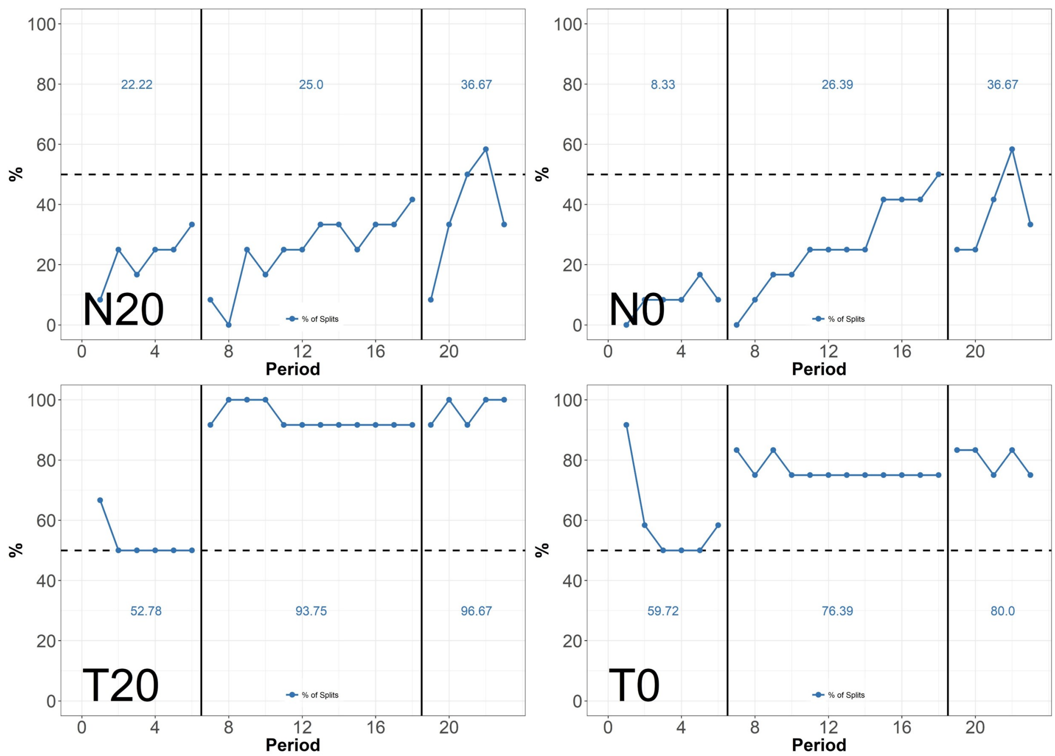
[13]For feedback induced effects on collusion in Cournot markets see Gomez-Martinez *et al.* (2016).

[14]See Appendix C.3 on the independence of market level observations.

3.5.1 Market states

Coordination on identical prices is naturally easier if one can communicate. Hence, market states in which a market is monopolized by either of the two firms should be less frequent if firms indeed talk. This is also observable in the data (see Figure 3.1). If firms communicate (T20, T0), market states of a split are more frequent (χ^2 test, all $p < 0.01$) and exhibit no systematic time trend, that is, there is no significant correlation between the number of splits and the period number (Kendall's τ, all $p > 0.05$). Although the correlations are not significant in the first supergames of T20 and T0, it seems that coordination starts at a high frequency but breaks down rapidly after the first period of play. Whether this could be driven by subjects' communicated content will be discussed in the text-mining analysis in Appendix C.4. If firms cannot communicate, however, market splits seldom occur at the start but become more frequent over the course of most supergames in N20 and N0 (Kendall's τ, $p < 0.05$ for SG_1 & SG_2 in N20 and SG_2 in N0). This process culminates up to parity of market states in the second supergames, and even to a majority of splits during the third.

Figure 3.1: Timetrends of market splits



Notes: Observed frequencies of market sharing are displayed over the course of each supergame. Annotations provide average empirical probability of occurence for a market sharing outcome.

The cause for market splits becoming gradually more frequent in N20 and N0 can be twofold. Either this is driven by an increasing number of markets that manage to coordinate on a common price and sustain it once they reach it, or by markets on which market states alternate and splits become just more frequent. Both possible explanations should be identifiable in first order Markov transition matrices which are shown in Table 3.2.

Table 3.2: Market state transition matrices in N20 and N0

N20	**to Split**	**to Monop.**
from Split	67.21%	32.79%
from Monop.	16.76%	83.24%
N0	**to Split**	**to Monop.**
from Split	80.0%	20.0%
from Monop.	10.27%	89.73%

The probabilities along the main diagonal are quite large in both treatments. Hence, market states are rather recursive and the likelihood of observing the same market state on a specific market repeatedly is high. To be precise, market demand is repeatedly split in 67% in N20 and 80% in N0 while repeated monopolization occurs in 83% and 90%. Aside from almost a third of all split markets in N20 that move towards monopolization (33%) the next period, transitions between market states are less frequent and overall mobility is low.

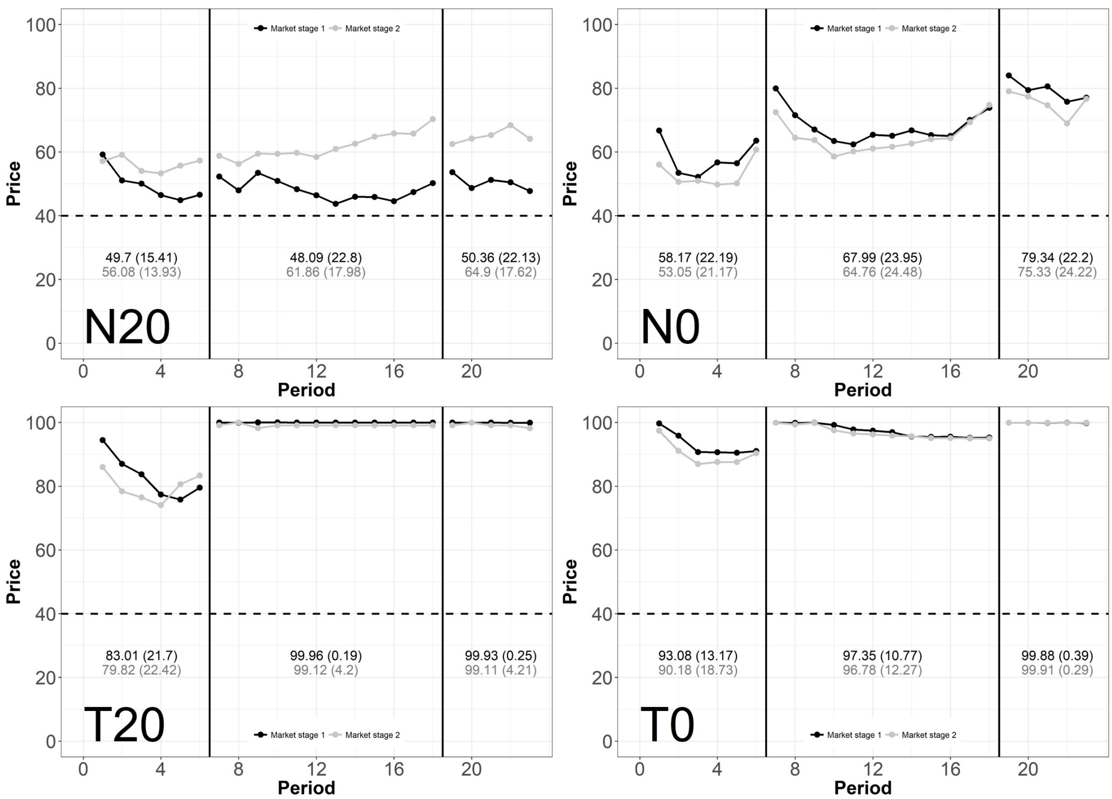
Firms on non-moving markets are either satisfied with the status quo or want to move but find it difficult to do so. Transition difficulties should, however, only be an issue if firms want to coordinate on a common price originating from monopolization. If the market is already split, firms usually can unilaterally alter this in charging any price other than the previous one (profitably a lower one). Thus, we generally deduce that firms find it indeed profitable to split market demand in the first market stage and compete within a symmetric market environment in $k = 2$.

3.5.2 Price level

Our first main result stems from the pairwise comparison of mean prices and subgame specific price levels in treatments N20 and N0. Figure 3.2 displays the development of mean market stage prices over all supergames.

Mean prices in $k = 1$ are significantly lower in N20 compared to N0 (two-sided Wilcoxon-Mann-Whitney U (WMW), all supergames $p < 0.05$). This downward pressure on prices is not only an aggregate effect but is present in all subgame dimensions. Price levels at which the market is split, monopolized and price levels of firms who are undercut, are all significantly lower (WMW, all $p < 0.01, 0.01, 0.05$). Figure 3.3 shows subgame specific prices in non-communication treatments. Firms' "investment" motive in N20 is especially pronounced in mean prices of monopolists who price just

Figure 3.2: Mean prices by treatments



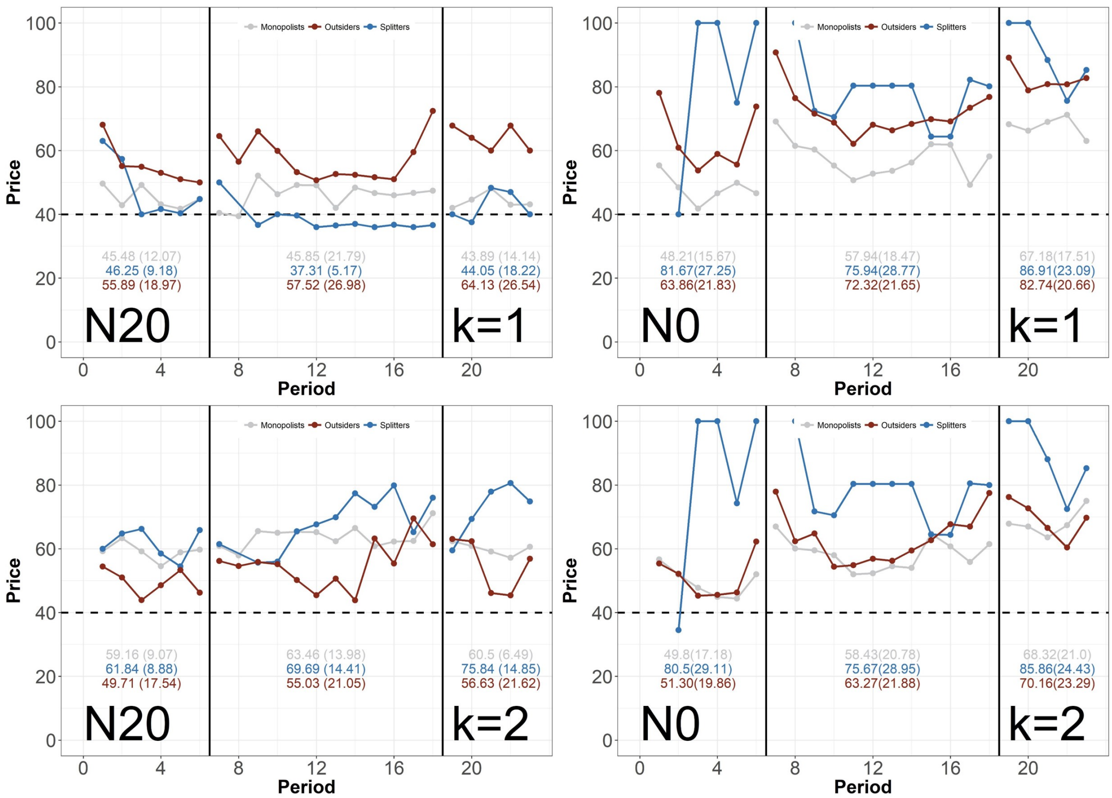
Notes: Mean prices in each market stage and period of play for all treatments and across all different subgames. Black data points correspond to prices of the first market stage ($k = 1$), while grey data correspond to the second ($k = 2$). Annotations provide mean supergame prices (standard deviations based on market averages in parenthesis).

above marginal cost and splitters who even price below that threshold in the second supergame. If switching costs are zero however (N0), firms who coordinate on common prices do so at prices which even exceed those of outsiders who overprice their fellow competitors.

Proceeding from the investment pattern in $k = 1$ of N20, firms also raise prices in $k = 2$. This is especially true for monopolists (Wilcoxon signed-rank test (WSR), all $p < 0.01$) and for firms that split market demand beforehand (WSR, all $p < 0.05$). Naturally, outsiders who initially overpriced have no incentive to do so and prices are not significantly different to those of $k = 1$ (WSR, all $p > 0.1$).
If switching costs are absent, monopolists and splitting firms price almost identically as in $k = 1$ (WSR, all $p > 0.1$) and only outsiders adapt prices downwards (WSR, all $p < 0.05$).

The treatment comparison of $k = 2$ in N20-N0 completes our first main result. Mean prices of $k = 2$ in N20 (towards locked-in consumers) are not significantly different compared to the price level in N0 (WMW, all $p > 0.1$).

Figure 3.3: Mean prices for non-communication treatments by subgames



Notes: Mean prices in each subgame and period of play for non-communication treatments. Data points in grey, blue and red correspond to prices of monopolists, splitters and firms who have been undercut in $k = 1$ respectively. Annotations provide mean supergame prices in each subgame (standard deviation based on market averages in parenthesis). N20: 12,12,11 market obs. of monopolization; 8,9,8 market obs. of splits. N0: 12,12,9 market obs. of monopolization; 3,9,8 market obs. of splits.

Result 1 *In N20, switching costs induce firms to sell at lower prices in $k = 1$ but the price level towards old consumers ($k = 2$) is not different compared to N0.*

The pairwise comparison between N20 and T20 as well as N0 and T0 produce our second result. We find strong evidence that communication increases firms' ability to sustain a higher price level (WMW, all $p < 0.01$). Although we observe prices declining in the first supergame of either communication treatment (see Figure 3.2), free-form multilateral communication is still effective. Further, price levels are not significantly different in T20 and T0 (WMW, all $p > 0.1$). This holds for prices aggregated over subgames as well as subgame specific prices. Hence, communication enables firms not only to raise prices generally but also to overcome the switching cost induced "investment" pressure which is dominant if communication is not possible.

Result 2 *Price levels are higher if firms can communicate. Switching costs have no competitive effect if firms are communicating.*

3.5.3 Distributional characteristics

Although switching costs have no significant effect on the price level in $k = 2$, that is, the price level faced by locked-in consumers, they do seem to have a negative effect on the price variance in specific subgames in N20 and N0. This is the case for prices on split markets in $k = 1$ (Fligner-Killeen (FK), SG_2 & SG_3: $p < 0.05$) and monopolists' prices in $k = 2$ (FK, all $p < 0.05$). Possibly, the effect of switching costs on firms' price setting behavior is simply not fully captured by a rank based statistic and is rather characterized by higher moments of the observed price distribution and not just the mean.

Our third main result is derived from comparisons of empirical CDFs and estimated kernel densities (KDE). The observed price distributions in treatments T20 and T0 are virtually identical and feature the bulk of probability mass on p^{max} (Figure C.5). As a consequence, the price distributions are not different between T20 and T0 (Kolmogorov-Smirnov (KS), all $p > 0.1$) and, thus, switching costs have no effect on firms' price distribution if firms communicate. We, therefore, restrict the following analysis to the non-communication treatments N20 and N0. Figure 3.4 displays the empirical distribution of all posted prices in non-communication treatments and the corresponding KDEs.

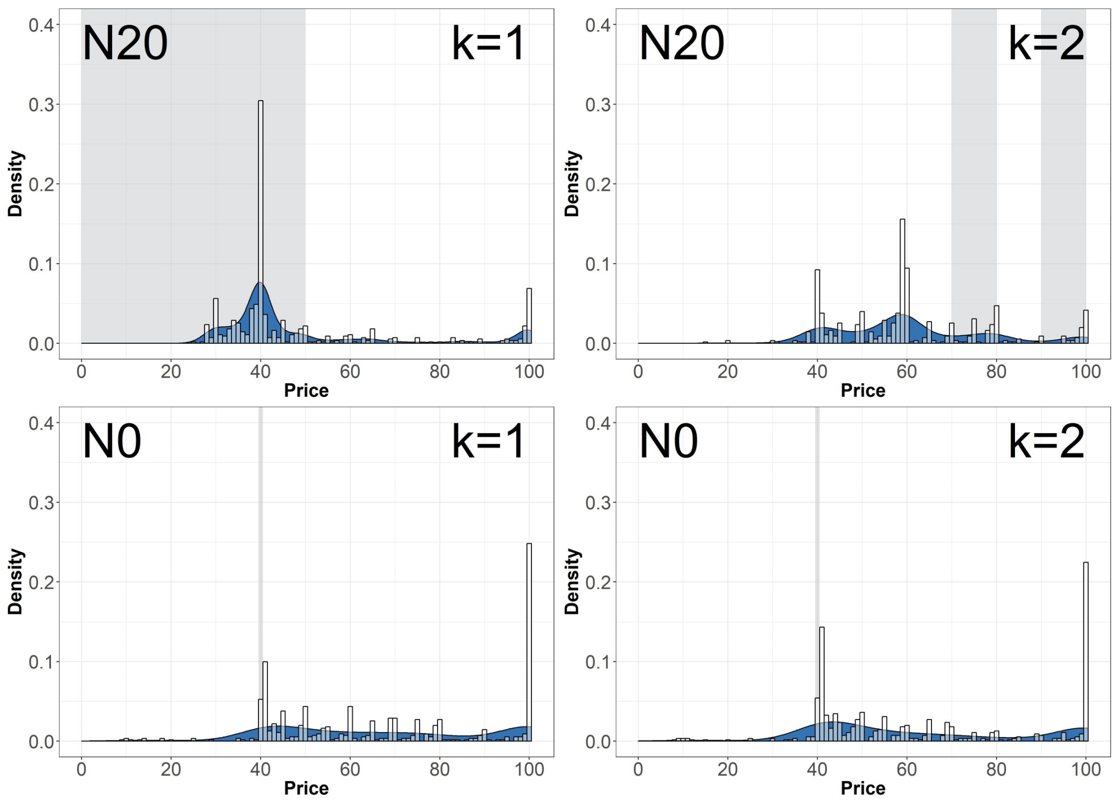
Switching costs have an effect on the price distribution in $k = 1$ (KS, all $p < 0.01$). This effect is driven by a twofold pattern. First, firms post fewer prices at p^{max} (6.9%) in N20 whereas it accounts for the highest probability mass (24.5%) in N0 (χ^2 test, all $p < 0.05$). Second, prices are more concentrated around marginal costs of $c = 40$ with 39.0% of observations within $[39, 41]$. In N0 prices are more uniformly distributed above marginal cost level as only 15.4% price such as $p_1 \in [39, 41]$ (χ^2 test, all $p < 0.01$).

The concentration of probability mass around marginal costs in $k = 1$ also occurs if we filter for prices at which the market is successfully monopolized (Figure 3.5) and split (Figure 3.6). Apart from the first supergame, price distributions of monopolists are again different (KS, SG_2 & SG_3: $p < 0.05$). In N20, those firms invest in a high market share with 32.7% of prices close to marginal cost level ($p_1 \in [39, 41]$). In contrast to this, monopolists in N0 price only in 17.6% of all cases within $[39, 41]$ which would relate to the static Nash prediction (χ^2 test, $p < 0.01$). In 79.2% of the cases, however, they manage to monopolize the market with prices above this threshold.

If we consider split markets, we identify prices around marginal costs as focal point for coordination in $k = 1$. Given that price distributions are different (KS, SG_2 & SG_3: $p < 0.01$), 68.9% of market sharing firms in N20 coordinate on prices within $[39, 41]$ whereas only 27.3% do so in N0 (χ^2 test, all $p < 0.05$). Contrary to this, coordination in N0 rather happens at p^{max} (63.6%).

We now turn to the distributional effects of switching costs in $k = 2$. The first thing to notice is that firms in N0 price almost identically to the first market stage.

Figure 3.4: Price distributions in N20 & N0 with KDEs



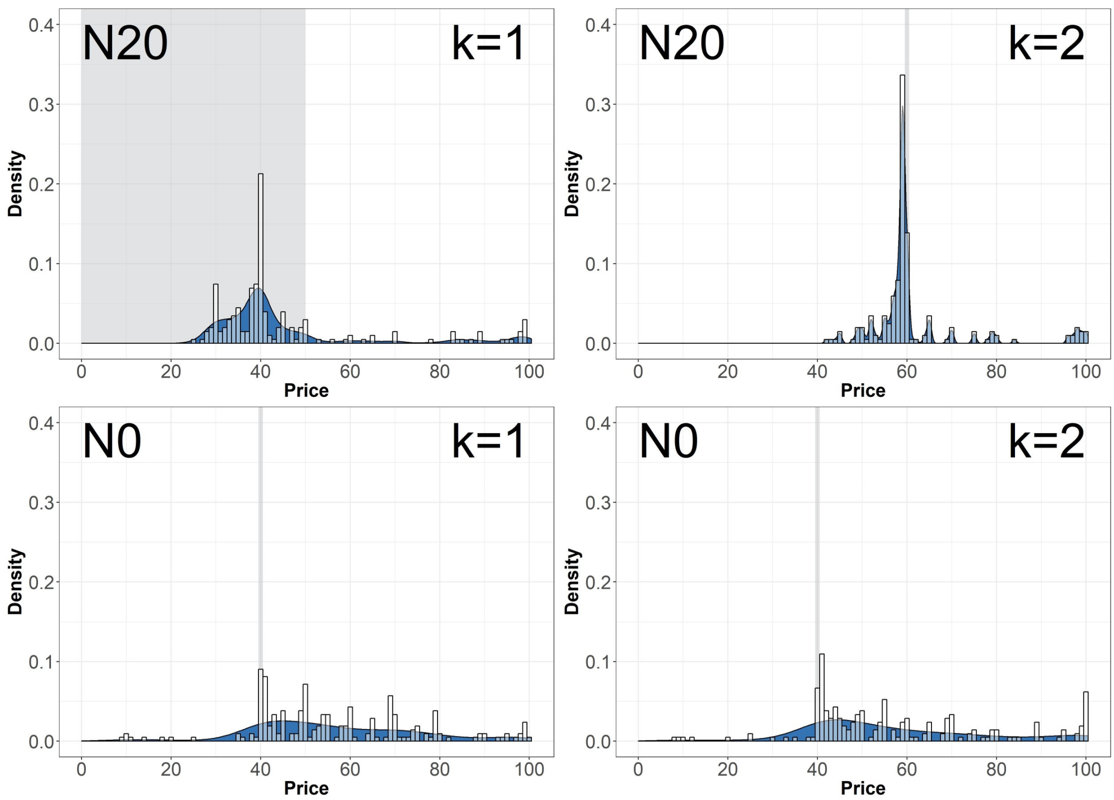
Notes: Displayed distributions incorporate posted prices in all supergames and across all subgames. Grey highlighted areas correspond to prices of the subgame perfect Nash equilibrium of the static game. Kernel densities are estimated via the Gaussian Kernel function and bandwidth is one standard deviation of the kernel.

Distributions of prior monopolists (KS, all $p > 0.1$) and of firms who previously split market demand are not significantly different (KS, all $p > 0.1$). In N20, however, the unfiltered price distributions differ between markets stages (KS, SG_2 & SG_3: $p < 0.01$). We identify a distinct trimodality with concentrations in proximity to $p_2 = \{40, 60, 80\}$ (Figure 3.4). These concentrations can be linked to the pricing incentives in the three different subgames of $k = 2$.

Monopolists' price distributions in $k = 2$ are different from those in N0 (KS, all $p < 0.1$). In N20 they frequently (47.5%) choose prices of $p_2 \in [59, 60]$ and, therefore, price according to the static Nash prediction (Figure 3.5). Given a rival's rationality, these monopolists effectively harvest their existing customers while not loosing demand to their rival. In N0, however, only 18.8% of prior monopolists play according to the static Nash prediction and choose a price of $p_2 \in [39, 41]$. These proportions of static equilibrium play are significantly different between N20 and N0 (χ^2, all $p < 0.01$) and form the second half of our third main result.

The fact that monopolists frequently "harvest" according to the static Nash equilibrium coincides with the pricing behavior of firms who were previously driven out of the market (see Figure C.6). 34.2% of these outsider firms price such as $p_2 \in [39, 41]$

Figure 3.5: Monopolists' price distributions in N20 & N0 with KDEs



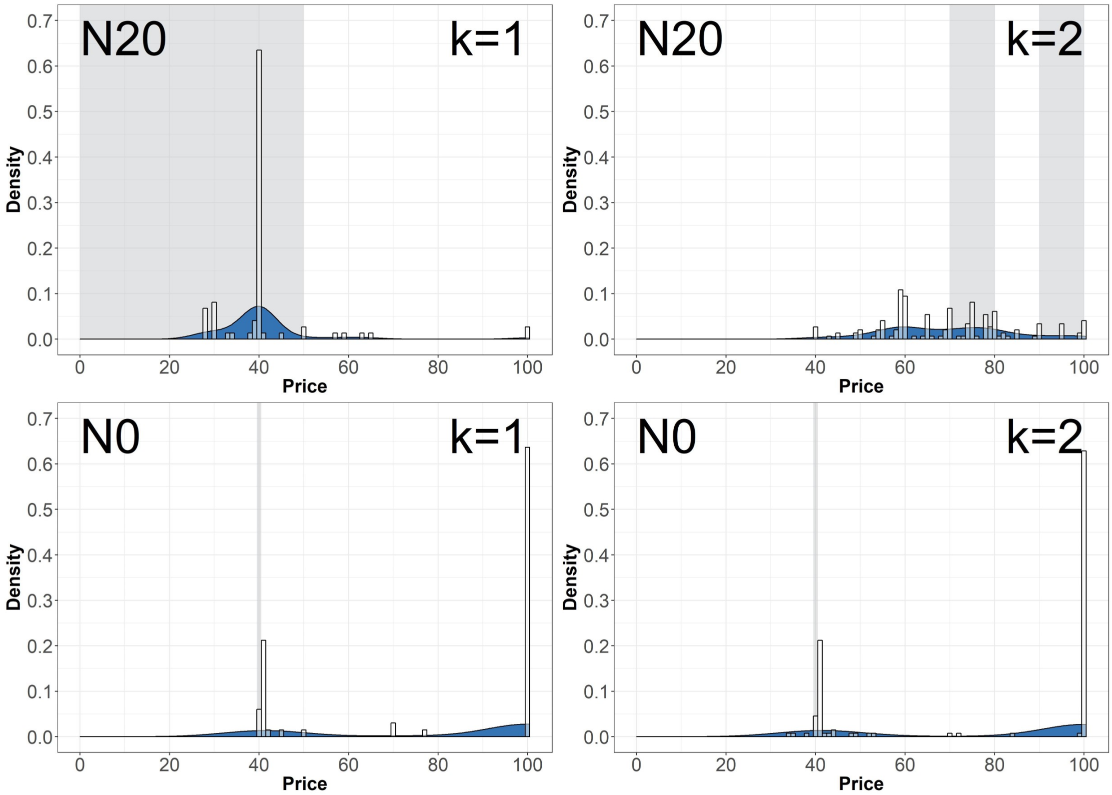
Notes: Displayed distributions incorporate posted prices in all supergames of firms who monopolize the market in the first market stage. Grey highlighted areas correspond to prices of the subgame perfect Nash equilibrium of the static game. Kernel densities are estimated via the Gaussian Kernel function and bandwidth is one standard deviation of the kernel. N20: 12,12,11 market obs. of monopolization; 8,9,8 market obs. of splits. N0: 12,12,9 market obs. of monopolization; 3,9,8 market obs. of splits.

and are restricting the monopolist maximally while securing themselves a non-negative payoff in case they win over some customers. The majority (56.9%) prices above that corridor following no systematic pattern. Outsiders' price distributions in N20 are not significantly different from those of N0 though (KS, all $p > 0.1$).

While the KDEs for monopolists and outsiders are unimodal, split markets exhibit a bimodal estimate. Probability mass agglomerates around values of $p_2 = \{60, 80\}$ (Figure 3.6) which corresponds to the maxima of the unfiltered KDE. 62.2% of market sharing firms choose prices of $p_2 > 60$ in $k = 2$ and thus price higher than the vast majority of monopolists. Apparently, subjects notice a rival's increased opportunity cost of pricing aggressively if both firms are equipped with an existing customer base. However, the observed bimodality does not coincide with the two disjoint price sets of the static Nash equilibrium in mixed strategies. Although the price distributions in split markets in N20 and N0 are visually different in $k = 2$, differences are statistically not significant (KS, all $p > 0.1$).[15]

[15]Since we do not observe split subgames on every market in every supergame, the statistical test

Figure 3.6: Splitters' price distributions in N20 & N0 with KDEs



Notes: Displayed distributions incorporate posted prices in all supergames of firms who shared market demand in the first market stage. Grey highlighted areas correspond to prices of the subgame perfect Nash equilibrium of the static game. Kernel densities are estimated via the Gaussian Kernel function and bandwidth is one standard deviation of the kernel. N20: 12,12,11 market obs. of monopolization; 8,9,8 market obs. of splits. N0: 12,12,9 market obs. of monopolization; 3,9,8 market obs. of splits.

Result 3 *In N20, switching costs cause firms' price distribution in $k = 1$ to be more concentrated at marginal cost level ($p_1 \in [39, 41]$) while they induce monopolists to price in closer proximity to the static equilibrium price level in $k = 2$ compared to N0.*

3.5.4 Profits, competitiveness & collusion

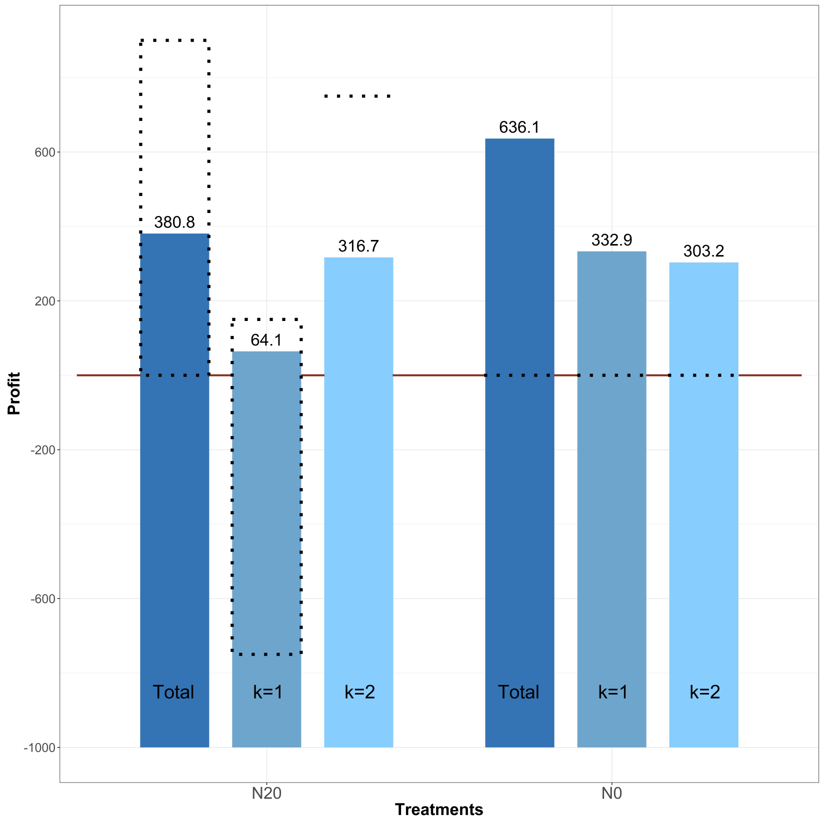
The competitiveness of a market and its scope for collusion is mainly indicated by the profits firms are able to realize. Our first two main results with respect to the price level carry over to the profit dimension (Table C.7). Firms earn significantly less in $k = 1$ of N20 (WMW, all $p < 0.1$) whereas profits in $k = 2$ are equivalent to those of N0 (WMW, SG_2 & SG_3 : $p > 0.1$).

From these observed profits we can now infer supra-competitive profits to answer our formulated exploratory research question on the degree of tacit collusion. Given our

is performed on a reduced sample size. We observe split subgames in N20 on 8 markets in the first supergame, 9 in the second and 8 in the third. In N0 we observe 3,9 and 8 markets that exhibit split subgames.

interpretation of supra-competitive profits, a profit above static equilibrium level would be considered collusive, around the equilibrium level as competitive, whereas a negative equilibrium mark-up would indicate a somewhat over-competitive environment. For this, Figure 3.7 displays firms' mean profits of one playing period in N20 and N0 and relates these to the static Nash-equilibrium profits.

Figure 3.7: Mean and equilibrium period profits in N20 and N0



Notes: Profit bars display firms' mean period profits in each market stage. Black dotted lines and rectangles correspond to profits of the subgame perfect Nash equilibria of the particular game.

In N0, firms realize positive supra-competitive profits in either market stage and thus manage to establish a tacit collusive environment (WSR, all $p < 0.05$). In N20, however, profits are for one below the mixed strategy equilibrium profit in $k = 2$ (WSR, all $p < 0.01$) and for another within the set of equilibrium profits in $k = 1$.

The treatment comparison of supra-competitive profits between N20 and N0 produces the first half of our fourth main result. In $k = 2$ switching costs lead to a lower degree of tacit collusion as supra-competitive profits are significantly lower in N20 (WMW, all $p < 0.01$). We cannot provide such definite evidence for the collusion intensity in $k = 1$ since the comparison hinges on the choice of a competitive profit benchmark from the set of equilibrium profits in N20. If we take the highest equilibrium profit as reference, we assume a somewhat "friendly" competitive benchmark and find evidence that also supra-competitive profits from new consumers are significantly lower

(WMW, all $p < 0.01$). If the median or lower bound profit of the interval are taken as reference instead, intensity of tacit collusion either does not differ or is significantly higher in N20 (WMW, all $p < 0.1$).

The effect of switching costs on the overall level of tacit collusion, that is, over both market stages, is unambiguously negative. We find strong evidence that firms realize overall less supra-competitive profits in N20 if we take the median equilibrium profit as competitive benchmark (WMW, all $p < 0.01$). Even if we assume the lowest equilibrium profit and thus assume a fierce competitive benchmark, we find the degree of tacit collusion to be lower in the third supergame of N20 (WMW, $p < 0.05$).

Result 4.1 *Consumer switching costs reduce firms' supra-competitive profits and therefore the intensity of tacit collusion.*

While tacit collusion seems to be aggravated by the presence of switching costs, this has not necessarily to hold for the incentives to collude explicitly. In reality, a firm that engages in illegal communication simultaneously gives up the opportunity to collude only tacitly. Hence, the profit gains a firm is able to realize through such an explicit agreement should be the crucial decision factor.[16]

Building upon the degree of tacit collusion, the potential profit gains from explicit cooperation constitute our result on explicit collusion incentives. The In a difference-in-difference OLS-regression (Table C.6) we find for the second and third supergame the profit increase through communication to be more pronounced if switching costs are active. Hence, firms would profit more from communication in N20 than in N0 and have a stronger monetary incentive to collude explicitly.[17]

Result 4.2 *Consumer switching costs increase profit gains through communication and thus make explicit agreements more attractive.*

3.6 Conclusion

Consumer switching costs induce an "invest-and-harvest" behavior in which new consumers are priced aggressively while less price sensitive existing customers are exploited. This in turn limits the interpretation of observed prices as indicator for the competitiveness of markets if one does not account for the countervailing pricing incentives. But which incentive dominates? How does the pressure to "invest-and-harvest" influence

[16] See Fonseca and Normann (2012) for a more extensive discussion of this.

[17] The contrary result in the first supergame can be mainly explained by subjects' inexperience and a lower price level in T20 relative to T0.

the potential for tacit collusion and from that possible gains through explicit communication? We address these questions by experimentally investigating Bertrand duopolies under both presence and absence of switching costs and both with and without the possibility to communicate.

We find that the "investment" incentive is dominant since switching costs reduce prices towards new consumers whereas price levels towards existing customers do not differ compared to an otherwise identical market. On such a reference market, firms manage to lift profits above the static equilibrium level and thus create a more tacitly collusive environment which they fail to do if switching costs are present. This is especially the case for firms who accomplish to initially serve all new consumers and possess a large customer base hereafter. Those monopolistic firms almost perfectly settle for safe equilibrium profits rather than trying to establish a tacit collusive outcome above equilibrium level. Opportunities for monopolists to do so are plenty however, as outsiders do not maximally restrict the monopolist in most of the cases and charge prices above marginal cost (56.93%). On the other hand, outsiders also have an incentive to raise a monopolist's profits since market interactions take place repeatedly and one time outsiders become monopolists themselves eventually.

The question why firms are not able to establish a comparable degree of tacit collusion remains puzzling. Seemingly, consumer switching costs induce firms to behave more competitively in general, whereas the atmosphere is more cooperative in markets without them. The prospect of looming asymmetries and the opportunity to gain a competitive advantage could drive the perception as rivals between the duopolists. Firms being symmetric throughout, however, contributes to a more cooperative view of the fellow duopolist.

The results raise in fact some doubts about the predominant view that markets are less competitive under switching costs (Beggs and Klemperer, 1992; Padilla, 1995). However, these good news regarding consumer harm involve a danger which Shapiro (1989, p.357) foreshadows with, "anything...that makes more competitive behavior feasible or credible actually promotes collusion".

Indeed, we find explicit communication not only to be an effective coordination device on more profitable outcomes in general (see Fonseca and Normann, 2012; Cooper and Kühn, 2014), but especially firms who are active on switching cost markets benefit even more from the possibility to communicate. To those firms explicit agreements seem more alluring since switching costs lower the degree of tacit collusion through intense competition for new consumers.

This trade-off between tacit and explicit collusion should be highly relevant in the field since firms who cartelize coincidentally reject the opportunity to collude tacitly. Our results suggest that the competition intensity for new consumers, that is, the "investment" price level, may be the decisive factor for the decision to cartelize. If new consumers in practice buy initially at unexpectedly high prices although a subsequent switch of suppliers is costly, this could indicate the existence of a dominant firm or an anti-competitive agreement. Hence, switching cost markets that exhibit competitively soft "investment" stages could be promising to investigate.

3.7 Appendix C

C.1 Profit function

We define firm i's profit in $k = 1, 2$ as

$$\pi_1^i = \begin{cases} \left(p_1^i - c\right) m & \text{if } p_1^i < p_1^j, \\ \frac{\left(p_1^i - c\right) m}{2} & \text{if } p_1^i = p_1^j, \\ 0 & \text{if } p_1^i > p_1^j. \end{cases}; \quad \pi_2^i = \begin{cases} \left(p_2^i - c\right) m & \text{if } p_1^i < p_1^j \wedge p_2^i < p_2^j + S, \\ \frac{\left(p_2^i - c\right) m}{2} & \text{if } p_1^i < p_1^j \wedge p_2^i = p_2^j + S, \\ 0 & \text{if } p_1^i < p_1^j \wedge p_2^i > p_2^j + S, \\ \left(p_2^i - c\right) m & \text{if } p_1^i = p_1^j \wedge p_2^i < p_2^j - S, \\ \frac{\left(p_2^i - c\right) 3m}{4} & \text{if } p_1^i = p_1^j \wedge p_2^i = p_2^j - S, \\ \frac{\left(p_2^i - c\right) m}{2} & \text{if } p_1^i = p_1^j \wedge p_2^j - S < p_2^i < p_2^j + S, \\ \frac{\left(p_2^i - c\right) m}{4} & \text{if } p_1^i = p_1^j \wedge p_2^i = p_2^j + S, \\ 0 & \text{if } p_1^i = p_1^j \wedge p_2^i > p_2^j + S, \\ \left(p_2^i - c\right) m & \text{if } p_1^i > p_1^j \wedge p_2^i < p_2^j - S, \\ \frac{\left(p_2^i - c\right) m}{2} & \text{if } p_1^i > p_1^j \wedge p_2^i = p_2^j - S, \\ 0 & \text{if } p_1^i > p_1^j \wedge p_2^i > p_2^j - S. \end{cases}$$

while corresponding profits of the rival j are derived analogously.

C.2 Proofs of Proposition 1-3

Proof of Proposition 1

Proof. Intuitively, a firm i who served the entire market demand in $k = 1$ will set a price of $p_2^i = p_2^j + S - \gamma$ that maximally exploits its own customer base while ensuring not to lose market share to its rival as long as $p_2^j \geq c - S + \gamma$ with $\gamma \to 0$. If a rival prices below this threshold a firm i will rather serve no consumers since maintaining some market share would result in negative profits. Hence, there exist multiple equilibria in pure strategies that imply prices of

$$p_2^i = p_2^j + S \in [c, c + S] \quad ; \quad p_2^j \in [c - S, c]$$

in which the monopolist realizes non-negative payoffs and the outsider zero profits. However, weak dominance or the trembling-hand equilibrium refinement produces the known price equilibrium of Klemperer (1987b, Section 2) and Farrell and Klemperer (2007, Section 2.3.1)

$$p_2^{i^{MI}} = p_2^j + S = c + S; \quad p_2^{j^{MI}} = c \, . \tag{C.10}$$

This completes the proof. □

Proof of Proposition 2

Proof. Given firm i's installed customer base in a split subgame, her options are to optimally "harvest" existing customers with $p_2^i = p_2^j + S - \gamma$, win half of the rival's customers with $p_2^i = p_2^j - S$ or monopolize the entire market at $p_2^i = p_2^j - S - \gamma$ for $\gamma \to 0$. However, profits in states in which firm i serves one quarter ($\pi_2^{i^{S,\frac{1}{4}}}$) or three quarter of market demand ($\pi_2^{i^{S,\frac{3}{4}}}$) can be characterized as irrelevant alternatives in terms of equilibria finding. Losing all prior market share due to overpricing the rival serves as a zero profit benchmark for firm i.

Figure C.1 displays firm i's profits in a split subgame as a function of rival j's price ($\pi_2^i(p_2^j)$). Intercepts of the profit functions determine the relevant cut-offs for the characterization of firm i's best response. A firm i will find it profitable to undercut any rival's price above $p_2^{j'}$ which satisfies

$$\pi_2^{i^{S,MI}} \geq \pi_2^{i^{S,S}} \iff (p_2^j - S - \gamma - c)m \geq (p_2^j + S - \gamma - c)\frac{m}{2}$$

and can be solved to be $p_2^{j'} = 3S + c^i + \gamma$. However, for $p_2^{j'}$ to be the relevant cut-off price it is required that $p_2^{j'} < p^{max} - S + \gamma$ such that a firm i can alternatively "harvest" its existing consumers with a full mark-up of S while not exceeding the reservation price. Given **Assumption 1**, this condition, however, is violated and firm i can only set a price of $p_2^i = p^{max}$ in that case. This, consequently, reduces the attractiveness of "harvesting" and shifts the rival's price for which undercutting is profitable ($p_2^{j''}$) downwards. It is then defined as a solution to

$$\pi_2^{i^{S,MI}} \geq \pi_2^{i^{S,S\ max}} \Leftrightarrow (p_2^j - S - \gamma - c)m \geq (p^{max} - c)\frac{m}{2}$$

with $\pi_2^{i^{S,S\ max}}$ as the maximum profit a firm i can realize if the market is split in $k = 2$. The solution to this inequality is $p_2^j \geq \frac{p^{max}+2S+c+2\gamma}{2} = p_2^{j''}$ and $[p_2^{j''}, p^{max}]$ defines rival's prices for which firm i finds it profitable to undercut.[18] Hence, for $\gamma \to 0$ a firm i finds it optimal to undercut rival's prices of

$$\frac{p^{max} + 2S + c}{2} \leq p_2^j \leq p^{max}.$$

The uniqueness of derived intercepts and cut-offs is secured by $\frac{\partial \pi_2^{i^{S,MI}}}{\partial p_2^j}, \frac{\partial \pi_2^{i^{S,\frac{3}{4}}}}{\partial p_2^j}, \frac{\partial \pi_2^{i^{S,S}}}{\partial p_2^j}, \frac{\partial \pi_2^{i^{S,\frac{1}{4}}}}{\partial p_2^j} > 0$.

Following this, one can state firm i's best response function as follows.

$$BR^{i^S}(p_2^j) = \begin{cases} p_2^j - S & \text{if } \frac{p^{max}+2S+c}{2} \leq p_2^j \leq p^{max}, \\ p^{max} & \text{if } p^{max} - S < p_2^j < \frac{p^{max}+2S+c}{2}, \\ p_2^j + S & \text{if } c - S \leq p_2^j \leq p^{max} - S, \\ p_2^i \in [c, p^{max}] & \text{if } p_2^j < c - S. \end{cases} \tag{C.11}$$

Applying the strict dominance criterion to the firms' best response functions, we can derive two disjoint sets of non-dominated prices firm i chooses with different intention. First, the range of "aggressive" prices **A** defined as

$$\mathbf{A} = \left[\underline{\alpha}, \bar{\alpha}\right] = \left[\frac{p^{max} + 2S + c}{2} - S - \gamma, p^{max} - S - \gamma\right]$$

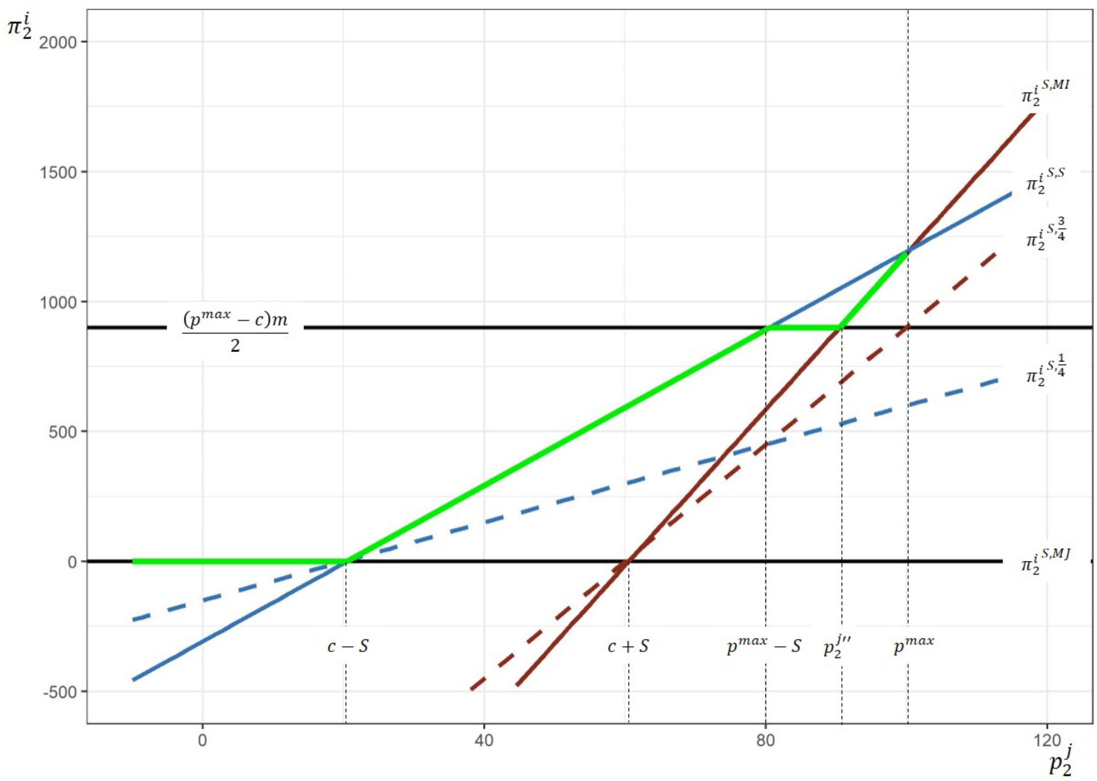
a firm i would set in order to win over market share. Second, the set of "harvesting" prices **H** which is given as

$$\mathbf{H} = \left[\underline{\epsilon}, \bar{\epsilon}\right] = \left[\frac{p^{max} + 2S + c}{2} - \gamma, p^{max}\right].$$

The latter one includes mainly the best responses on rival's aggressive prices. Please note that a price of $\bar{\epsilon} = p^{max}$ is firm i's best response on a rival's harvesting price that is just not profitable to undercut ($p_2^j = \underline{\epsilon}$). For every rival's harvesting price, except for

[18] The condition of $S \leq \frac{p^{max}-c}{2}$ in **Assumption 1** secures that there is at least one price for which it is profitable to price aggressively and that $[p_2^{j''}, p^{max}]$ is a non-empty set.

Figure C.1: Firm i's profits and best responses in a split subgame



Notes: The displayed profit lines incorporate the experiment parameter values of $S = 20$, $c = 40$, $m = 30$, $p^{max} = 100$. Intercepts are provided for $\gamma \to 0$. A firm i's best response profits are colored in green.

$\underset{\tilde{}}{\epsilon}$, there exists an aggressive price in $\mathbf{A}$ firm i chooses to optimally undercut the rival. Thus, for $\gamma \to 0$ the interval length of $\mathbf{A}$ corresponds to the length of $\mathbf{H}$. Equation (C.12) then defines firm i's best response after the iterated elimination of strictly dominated prices $BR^{i^{S*}}(p_2^j)$ and consequently constitutes firm i's set of rationalisable price strategies in a split subgame.

$$BR^{i^{S*}}(p_2^j) = \begin{cases} \mathbf{A} & \text{if } p_2^j \in \left]\underset{\tilde{}}{\epsilon}\,;\bar{\epsilon}\right], \\ \left[\underset{\tilde{}}{\epsilon}\,;\bar{\epsilon}\right[& \text{if } p_2^j \in \mathbf{A}, \\ \bar{\epsilon} = p^{max} & \text{if } p_2^j = \underset{\tilde{}}{\epsilon}. \end{cases} \tag{C.12}$$

The price spectrum of aggressive and harvesting prices does not exhibit any states of mutual best responses in pure pricing strategies. Hence, firm i randomizes over the two disjoint sets of rationalisable strategies $p_2^i \in \mathbf{A}\dot{\cup}\mathbf{H}$ which constitutes an equilibrium in mixed strategies we define as Γ. Since $p_2^i = \underset{\tilde{}}{\epsilon}$ is not profitable to undercut, firm i will always retain it's market share and will realize the same profit, even if the rival optimally responds with $p_2^j = \bar{\epsilon}$. As a consequence, it must retain the same expected profit as well in the mixed strategy equilibrium such that $E[\pi_2^i(\Gamma)] = \pi_2^i(p_2^i = \underset{\tilde{}}{\epsilon})$ which converges to

$$\pi_2^{i^S} = \left(\frac{p^{max} + 2S + c}{2} - c\right)\frac{m}{2} = \left(\underline{\epsilon} - c\right)\frac{m}{2} \tag{C.13}$$

for $\gamma \to 0$. This completes the proof. □

Proof of Proposition 3

Proof. Firms are anticipating market outcomes of $k = 2$ competition and maximize combined profits from both market stages in $k = 1$. We define $\Pi^{i^{MI}} = \pi_1^{i^{MI}} + \pi_2^{i^{MI}}$ as firm i's total profit if it monopolizes the market in the first period. Total profits of $\Pi^{i^S}; \Pi^{i^{MJ}}$ are defined analogously. It is obvious that a firm wants to avoid overpricing its competitor in $k = 1$, since this implies zero profits in either market stage. However, this case is highly relevant because it always secures a non-negative payoff and serves as a minimum profit benchmark. The intercepts of total profits conditional on a rival's price constitute the proposition. Firm i's total profits are defined as

$$\begin{aligned}
\Pi^{i^{MI}} &= \pi_1^{i^{MI}} + \pi_2^{i^{MI}} = \left((p_1^j - \gamma) - c\right)m + S \cdot m \\
\Pi^{i^S} &= \pi_1^{i^S} + \pi_2^{i^S} = \left(p_1^j - c\right)\frac{m}{2} + \left(\underline{\epsilon} - c\right)\frac{m}{2} \\
\Pi^{i^{MJ}} &= \pi_1^{i^{MJ}} + \pi_2^{i^{MJ}} = 0 + 0\,.
\end{aligned}$$

The intercepts of *(i)* $\Pi^{i^S}(p_1^j) \geq \Pi^{i^{MJ}}(p_1^j)$ and *(ii)* $\Pi^{i^{MI}}(p_1^j) \geq \Pi^{i^{MJ}}(p_1^j)$ determine for which rival's prices profits are greater than zero while *(iii)* $\Pi^{i^{MI}}(p_1^j) \geq \Pi^{i^S}(p_1^j)$ determines when it is profitable to monopolize rather than splitting the market in $k = 1$. The solutions to the above inequalities for $\gamma \to 0$ are as follows:

(i)

$$p_1^j \geq 2c - \underline{\epsilon}\,,$$

(ii)

$$p_1^j \geq c - S\,,$$

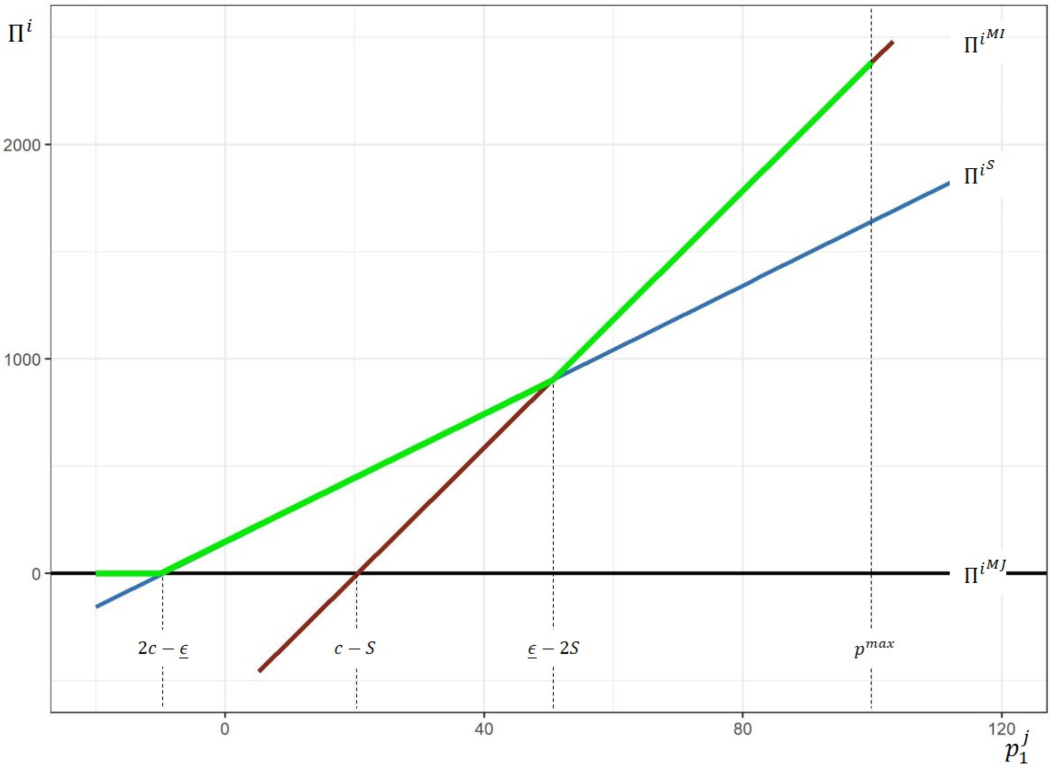
(iii)

$$p_1^j \geq \underline{\epsilon} - 2S\,.$$

Given **Assumption 1**, one can show that the derived thresholds can be ordered such as $(i) < (ii) < (iii)$. Since $\Pi^{i^{MI}}$ and Π^{i^S} are both monotonically increasing functions in p_1^j the derived intercepts are unique. Hence, for rival's prices of

$$p_1^j \in \left[2c - \underline{\epsilon}\,;\ \underline{\epsilon} - 2S\right] \tag{C.14}$$

Figure C.2: Profits of the reduced switching cost game



Notes: Firms' total profits of the reduced form game in case of market sharing (Π^{i^S}), own and rival's monopolization ($\Pi^{i^{MI}}$, $\Pi^{i^{MJ}}$) as a function of rival's price (p_1^j). Firm i's best response profits are highlighted in green.

total profits of sharing the market in $k = 1$ are positive and exceed those from own monopolization. Consequently, if the rival chooses a price within the above interval, firm i rather wants to price identical $p_1^i = p_1^j$ and split market demand. This implies the existence of multiple subgame perfect Nash equilibria in pure price strategies. In equilibrium total profits are of the interval

$$\Pi^{i^*} \in \left[0, 2\left(\underline{\epsilon} - c - S\right)\frac{m}{2}\right] . \tag{C.15}$$

Figure C.2 illustrates firms' total profits of the reduced game and the relevant intercepts. This completes the proof. □

C.3 Analysis on the independence of market level observations

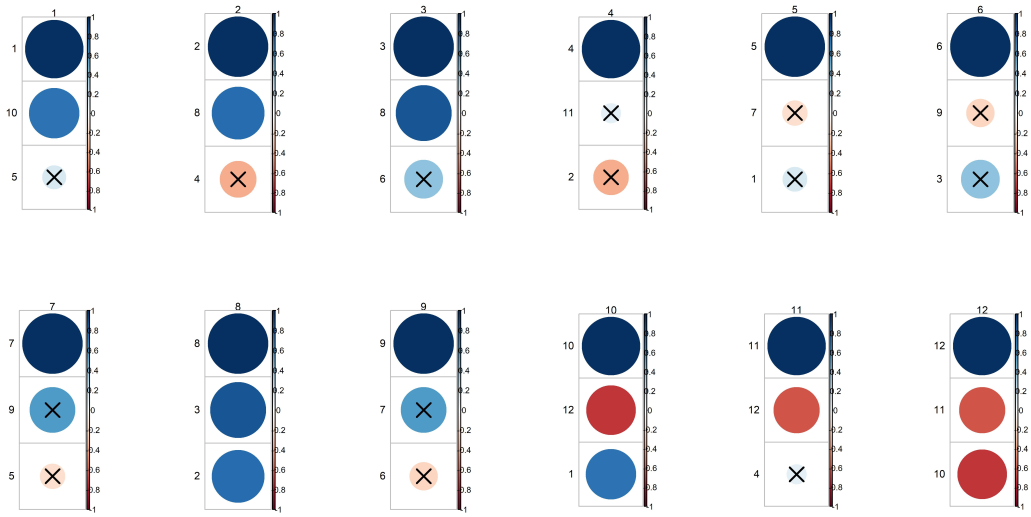
All conducted non-parametric analyses which are reported in Section 3.5 are based on market level data. This implies that each experimental market in each supergame is treated as an independent observation. This assumption, however, has to be supported by further analysis since subjects' price setting in supergames two and three may be influenced by prior experiences from interactions in supergames one and two.

The aim of this section is to show that within a supergame matched pairs of subjects, that is, experimental markets, can be seen as independent observations. Hence, there must not be a systematic correlation between market prices of prior partners from previous supergames. To be precise, consider market A in supergame two in which the exemplary firms i and j are active. Both firms where matched to two other subjects in the previous supergame and received feedback from this interaction. Let us assume firm i's prior partner is in supergame two now active in market B and j's prior partner in market C. For market A being considered as an independent observation, there must not be a systematic correlation in market prices to the markets B and C in the supergame two. This consequences that we need to compute the correlation coefficients for each of the 12 experimental markets towards their prior partner markets. In supergame two we have to consider two partner markets (from interactions in supergame one), whereas in supergame three this increases to four partner markets (from interactions in supergame one and two). Naturally, we do this analysis for each treatment separately.

Since we cannot assume that posted prices are normally distributed, we calculate Spearman's ρ as rank based correlation coefficient. The employed significance level for the analysis is 0.05. The correlation coefficients are calculated based on average prices from competition in $k = 1$. The analysis neglects prices from $k = 2$ since these are highly subgame dependent and bear not much information on inter market correlation. This produces for each experimental market a price set with length of the respective supergame, that is, 12 for the second supergame and 5 for the third, over which correlations are then computed.

The subsequent Figures C.3 and C.4 display the correlations of each of the 12 experimental markets to their prior partner markets in treatment N20. In the second supergame of N20 (Figure C.3) only three experimental markets exhibit significant correlations with both their partner markets. On all other markets at least one correlation coefficient is insignificant (crossed out dots). It can hardly be said that there is systematic and significant correlation between subjects that have previously interacted during a supergame. This becomes even more clear when we look at experimental markets in the third supergame of N20 and their correlations to markets of prior partners

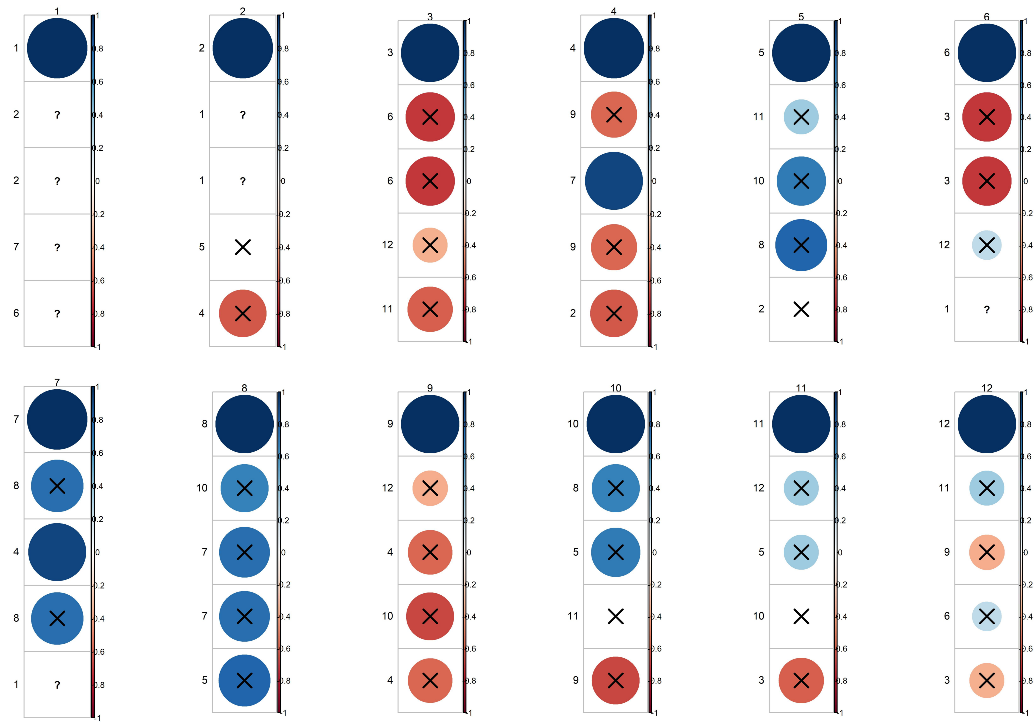
Figure C.3: Correlation towards prior partner markets in supergame two in N20



Notes: Correlation coefficients are displayed according to colored scaled points. The size of the dots as well as the color scale refers to the intensity and sign of the correlation. A crossed out dot refers to a correlation coefficient that is not significantly different from zero. The corresponding significance level is 0.05. A question mark indicates that the correlation coefficient cannot be computed because at least one of the groups exhibits an invariant price set.

from the previous two supergames. Figure C.4 reveals that only two markets exhibit at least one significant correlation with one of their partner markets. All other coefficients are either not significant or cannot be computed because one of the compared market exhibits invariant market prices (indicated by a question mark). This picture neither changes for treatment N0 (Figures C.7 & C.8) nor in the communication treatments T20 (C.9 & C.10) and T0 (C.11 & C.12). Hence, we cannot reject the null-hypothesis globally that the inter market correlation due to previous matches is different from zero. Therefore, we have no pressing concerns that hinder us in using experimental markets as unit of observations and basis for non-parametric statistical tests.

Figure C.4: Correlation towards prior partner markets in supergame three in N20



Notes: Correlation coefficients are displayed according to colored scaled points. The size of the dots as well as the color scale refers to the intensity and sign of the correlation. A crossed out dot refers to a correlation coefficient that is not significantly different from zero. The corresponding significance level is 0.05. A question mark indicates that the correlation coefficient cannot be computed because at least one of the groups exhibits an invariant price set.

C.4 Text analysis

The analysis in this section covers the second dimension of input subjects made during the experiment, that is chat content. We employ different approaches and metrics to quantify communication among subjects which contain descriptive statistics based on unsupervised message counts as well as text mining procedures. These results accompany findings of the prior quantitative analyses and should not be interpreted as causal relationships. We are primarily interested in whether communicated content differs in the presence of switching costs and even more so between the first supergame and the latter two in treatments T20 and T0 since these exhibit different patterns in distribution of market states.

Descriptives

In this section we provide descriptive statistics assessable by simply counting *messages* in the raw, unsupervised chat log.[19] We define a *message* as a line of text that is written by subject i and is sent coherently to subject j within an experimental market. Therefore, a message is interpreted as an unilateral contribution to the within market communication. Table C.1 displays mean message counts within a market for each supergame ($\overline{C}_{SG}$) and treatment. While we observe more overall interactions in T0,

Table C.1: Mean messages per market and supergame

Means of within market *messages*	T20	T0
$\overline{C}$	**12.83**	**14.5**
$\overline{C}_1$	10.75	11.5
$\overline{C}_2$	12.58	15.25
$\overline{C}_3$	15.17	16.75
Observations	462	522

the number of messages sent per supergame increases over the course of the experiment in both treatments. Especially in T0 chat interactions become more frequent after the first supergame. In the light of the market outcomes in the first supergame of both communication treatments, the lower amount of messages seems not surprising. Possibly subjects' communication was simply not extensive enough to establish stable collusion.

[19]The text data is unsupervised in the sense that neither punctuation and misspellings are corrected nor are *stopwords* filtered out. Stopwords are language specific and include words that are naturally used very frequently while not bearing any analytic value for the specific research question. For the English language these can be "a", "and", "also" or "the" among others. They are usually removed prior to text mining procedures in order to avoid any bias.

Text Mining

Whereas simple message counts only display how reciprocal a conversation might be, text mining methods allow a somewhat objective analysis of the communicated content. Based on our quantitative findings in Section 3.5 we are particularly interested whether communicated content differs between treatments and even more so whether content can indicate why collusion breaks down frequently in the first supergame compared to supergames two and three.

For this purpose we use the *Relative Rank Differential* (RRD) of Huerta (2008) which measures words that are relatively more frequent in one corpus of text compared to another.[20] Text mining methods so far have been mostly used in fields of computational linguistics and health sciences but recently also for the analysis of chat content in economic experiments (Möllers *et al.*, 2017).

The RRD statistic is calculated on word ranks according to their frequency in the respective corpus. For the ordinal measurement of words within a corpus we adopt the fractional ranking method ("1 2.5 2.5 4") for the RRD which is calculated according to (C.16).[21]

$$RRD_{w,t1} = \frac{r_{w,t2} - r_{w,t1}}{r_{w,t1}} \tag{C.16}$$

The expression $r_{w,t1}$ corresponds to the rank of word w in the base corpus $t1$ whereas $r_{w,t2}$ is the rank of the same word w in the comparison corpus $t2$. The RRD therefore accounts not only for the rank differential but also for the frequency of the respective word in the base corpus. Consequently, rank differences for common words are weighted higher than those that are only used rarely. The least common words of a corpus are sparse words which have zero frequency in that respective corpus but are used in the comparison one and have the rank of $\underline{r_w}$ of the ordinal spectrum. Naturally, a word w with a positive RRD value corresponds to a word which is ranked higher in the base corpus and the magnitude of the metric determines the salience or "keyness" of the respective word.

[20]The compared corpora of text do not necessarily correspond to text of different treatments but can also capture subsets of different market outcomes or other dimensions. In our case the respective first supergame and supergames two and three.

[21]The applied ranking method within the corpora naturally effects the ordinal spectrum $O = [\underline{r_w}, \overline{r_w}]$ and consequently the RRD. To conveniently compare ranking methods we provide a ranking of four items in which the first is ranked ahead while the last is ranked behind the second and third which are tied based on the ranking criteria. The standard competition ranking ("1224") and its modified version ("1334") are less condensing on O than the dense ranking ("1223") but the sum of assigned ranks varies with the number of ties. Especially for corpora containing only a limited amount of total words, like experiment chat, the probability of words having the same (low) frequency is quite high and the condensing effect is quite prevalent. Dense ranking would therefore severely reduce the ordinal spectrum to the number of different word frequencies we observe and consequently reduce the magnitude of the RRD. Therefore, we use fractional ranking ("1 2.5 2.5 4") as it is not only the least condensing method with respect to O but has also the property that the sum of all ranks is the same as in ordinal ranking ("1234") and independent of the number of ties which is needed for statistical tests.

As with other text mining procedures the RRD is calculated on supervised chat data to prevent any bias of the metric. For this we conduct the following modifications and filtration during a preprocessing stage. We remove any *punctuation* and *special characters* such as "@" or "/". Since capital letters are pretty common in the German language it is crucial to transform all letters to *lower case* to avoid a twofold listing of the identical word. Our vector of German specific *stopwords* which are filtered out includes all variations of conjunctions, definite and indefinite articles and prepositions of location. Finally, we correct common *misspellings*, *typos* and merge *colloquial words* accordingly.[22] We report keywords in Tables C.2-C.4 whose original rank in the base corpus and rank differential satisfies $r_{w,t1} \leq 50$ and $RRD_{w,t1} \geq 3$ respectively.

Table C.2: Keywords in whole treatments T20 and T0

$T20$		$W_{T20} = 1476$		$T0$		$W_{T0} = 1458$	
Word	Freq.	Rank	RRD to $T0$	Word	Freq.	Rank	RRD to $T20$
many	8	30.5	16.62	deal	10	26.5	19.57
market	8	30.5	16.62	switching costs	6	44	11.39
absolutely	6	42	11.80	per	17	11	8.45
bet	8	30.5	8.93	(each) time	13	17.5	8.40
say	6	42	6.21	I	7	37.5	7.56
sure	11	21.5	4.05	perfect	12	20	7.23
go	9	24.5	3.43	1800	10	26.5	5.21
have	7	36.5	3.21	shall	12	20	4.20
give	12	19	3.16				

Notes: Words are ordered according to the *RRD* towards the respective treatment which is calculated according to Equation C.16. Only words whose original rank in the base corpus ($t1$) and rank differential satisfies $r_{w,t1} \leq 50$ and $RRD_{w,t1} \geq 3$ are displayed. Punctuation, articles, conjunctions and prepositions of location are ommited. Words are translated from German.

The keyword comparison between treatments T20 and T0 in Table C.2 exhibits an almost identical number of total words ($W_{T20,T0}$) in both corpora. Keywords used under switching costs contain statements of affirmation like "sure" or "absolutely" and words corresponding to the experimental environment as "market", "bet" or "say". The same is true for keywords used in T0 as we find affirmations "perfect" or "deal" and words that are used to communicate strategies like "per" and "time" as in the expression "each time". Further, the phrase of "1800" is also salient and corresponds to a firm's period profit if the market is repeatedly split at p^{max}. This could indicate

[22]Colloquial speech that is transformed mostly contains all variations of negations ("nope", "nah") , affirmations ("yep", "yup", "yessir") and interjections of laughing and giggling ("haha", "tee-hee").

that subjects use explicit calculations and profit targets to communicate a strategy and compare between them.[23] However, we consider the keywords of both corpora as somewhat neutral in a sense that it is difficult to deduct any indication from them on observed outcomes that are not significantly different anyhow.

Table C.3: Keywords in the first supergame and the latter two of T20

SG_1			$W_1 = 393$	$SG_{2,3}$			$W_{2,3} = 1083$
Word	Freq.	Rank	RRD to $SG_2 3$	Word	Freq.	Rank	RRD to SG_1
attempt	3	26.5	18.30	many	8	21	18.76
(I) see	4	19.5	12.69	to me	8	21	18.76
know	2	45	10.37	none	8	21	18.76
were	2	45	10.37	has	8	21	18.76
suggest	2	45	10.37	absolutely	6	29	13.31
our	2	45	10.37	(we) both	6	29	13.31
get	2	45	10.37	super	13	12	8.83
half	2	45	10.37	total	8	21	4.62
(I) believe	2	45	10.37	always	39	3	4.50
900	4	19.5	5.59	have	6	29	3.07
choose	2	45	4.93				
already	2	45	4.93				
product	2	45	4.93				
costs	2	45	4.93				
(we) might	2	45	4.93				
you're welcome	2	45	4.93				
(I) think	2	45	4.93				
agree	3	26.5	3.85				

Notes: Words are ordered according to the *RRD* towards the respective supergame(s) which is calculated according to Equation C.16. Only words whose original rank in the base corpus ($t1$) and rank differential satisfies $r_{w,t1} \leq 50$ and $RRD_{w,t1} \geq 3$ are displayed. Punctuation, articles, conjunctions and prepositions of location are ommited. Words are translated from German.

Contrarily, market state proportions do differ between the first supergame and the latter two in both treatments. Table C.3 and C.4 display the keywords of the within treatment comparisons of supergames. What has already been indicated by the lower amount of *messages* sent in the respective first supergames translates also into total

[23]Interestingly, the word "switching costs" is more salient in N0 in which they are zero. However, this is due to one market in which subjects talk about the framing of the respective treatment and consequently use the specific word more frequently.

Table C.4: Keywords in the first supergame and the latter two of T0

SG_1			$W_1 = 386$	$SG_{2,3}$			$W_{2,3} = 1072$
Word	Freq.	Rank	RRD to SG_23	Word	Freq.	Rank	RRD to SG_1
would	3	28	17.21	has	13	11.5	34.78
that	4	18.5	13.00	have	7	27.5	13.96
price	7	10	10.70	more	6	31	12.27
suggest	2	49.5	9.30	exactly	6	31	12.27
test	2	49.5	9.30	per	16	9	12.11
idea	2	49.5	9.30	collusion	5	39	9.55
had	2	49.5	9.30	(it) worked	5	39	9.55
alternate	2	49.5	9.30	go	5	39	9.55
second	3	28	8.25	first	5	39	9.55
most	3	28	8.25	(I) am	5	39	9.55
switching costs	4	18.5	5.32	many	10	17	5.94
none	5	14	4.29	1800	9	20.5	4.76
probably	2	49.5	4.23	(we) both	8	24.5	3.82
kidding	2	49.5	4.23	if	13	11.5	3.30
reverse	2	49.5	4.23	always	34	4.5	3.11
tip	2	49.5	4.23				
next	2	49.5	4.23				
sounds (good)	2	49.5	4.23				
highest	2	49.5	4.23				
equally	2	49.5	4.23				
sense	3	28	3.18				
thanks	3	28	3.18				

Notes: Words are ordered according to the *RRD* towards the respective supergame(s) which is calculated according to Equation C.16. Only words whose original rank in the base corpus ($t1$) and rank differential satisfies $r_{w,t1} \leq 50$ and $RRD_{w,t1} \geq 3$ are displayed. Punctuation, articles, conjunctions and prepositions of location are ommited. Words are translated from German.

words used. Subjects do not only interact less prior to their first pricing decision but also use far fewer words on average compared to subsequent communication.

For keywords in T20 we find again somewhat neutral words such as "product", "costs" in SG_1 or affirmations , "super", in $SG_{2,3}$. However, the most salient keywords in the first supergame are either subjunctive, "were" or "(we) might", or noncommittal like "attempt", "suggest" or "(I) believe". Whereas in the subsequent supergames more binding words like "(we) both" and "always" are more salient. Apparently, communicated content in SG_1 is less definite and may indicate that subjects could be more uncertain about pricing decisions and the desirability of certain market outcomes due to somewhat vague communication.

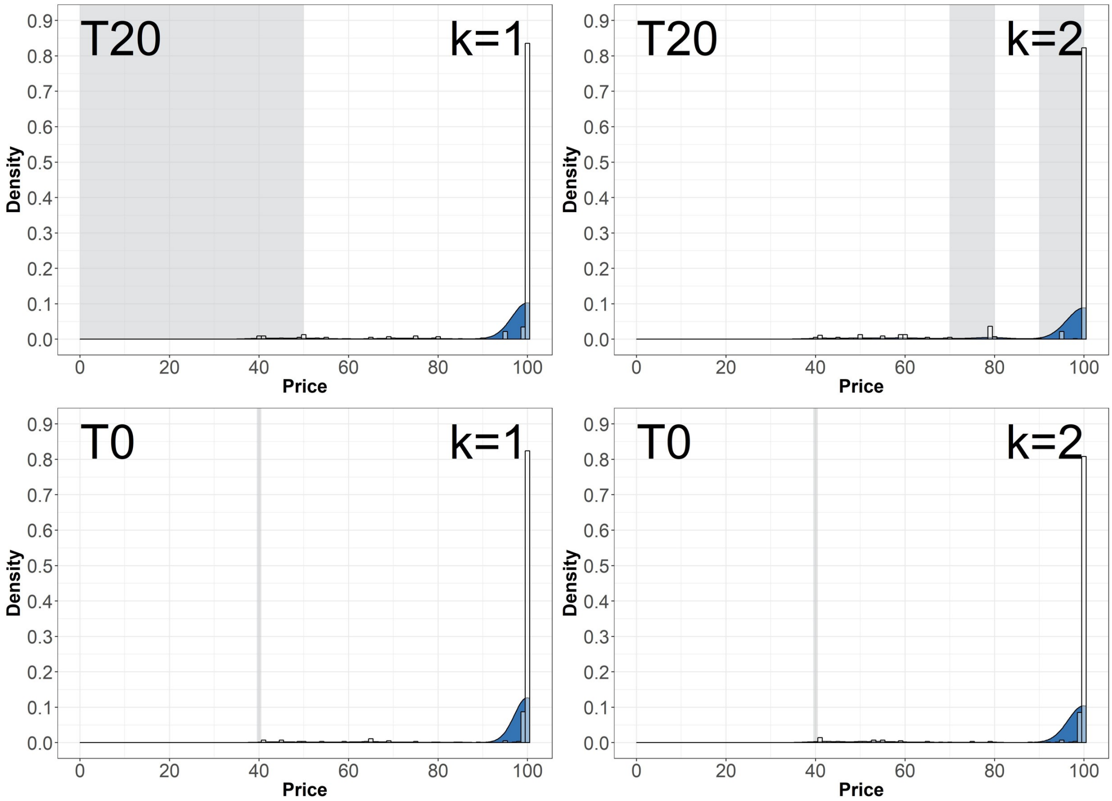
We observe the same increased keyness for subjunctive expressions and noncommittal language in the supergame comparison of T0. Again words like "would", "suggest", "test" and "idea" can be found at the top of the RRD ranking in SG_1 indicating that the lack of definite language is not treatment specific. It is rather driven by subjects' inexperience of what specifically needs to be communicated to create an environment of stable collusion. However, subjects seem to gain that experience after the first supergame. Keywords in $SG_{2,3}$ are then again "per", "always" and "1800" characterizing a more profound payoff evaluation but also "collusion" and "if" indicate more contingent price strategies. This is in line with findings of Cooper and Kühn (2014) who find that especially contingent messages including a punishment facilitate collusion.[24]

Hence, the prevalent noncommittal language together with fewer interactions in the respective first supergames provide an intuition why market outcomes are less collusive. It seems that subjects need to learn how to use communication effectively in order to establish stable collusion.

[24]Bochet and Putterman (2009) also find that communicated content affects subjects' play and that especially the threat of punishment as a contingency facilitates efficiency.

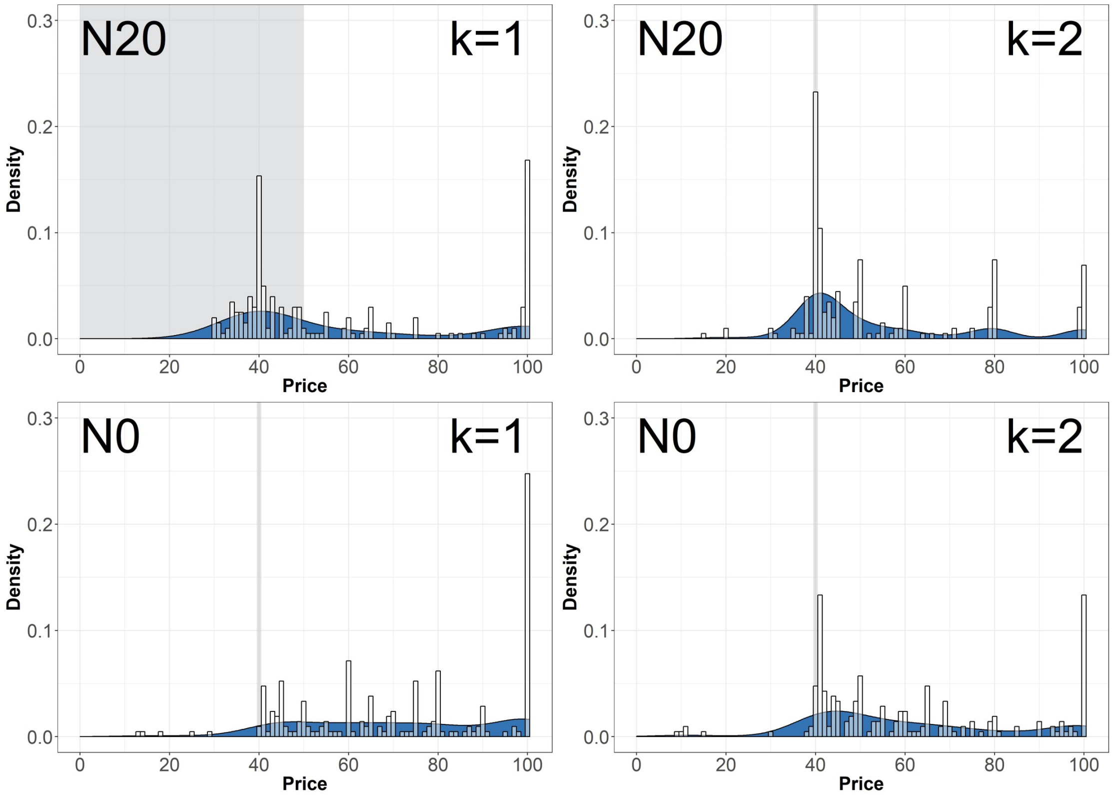
C.5 Figures & tables

Figure C.5: Price distributions of communication treatments



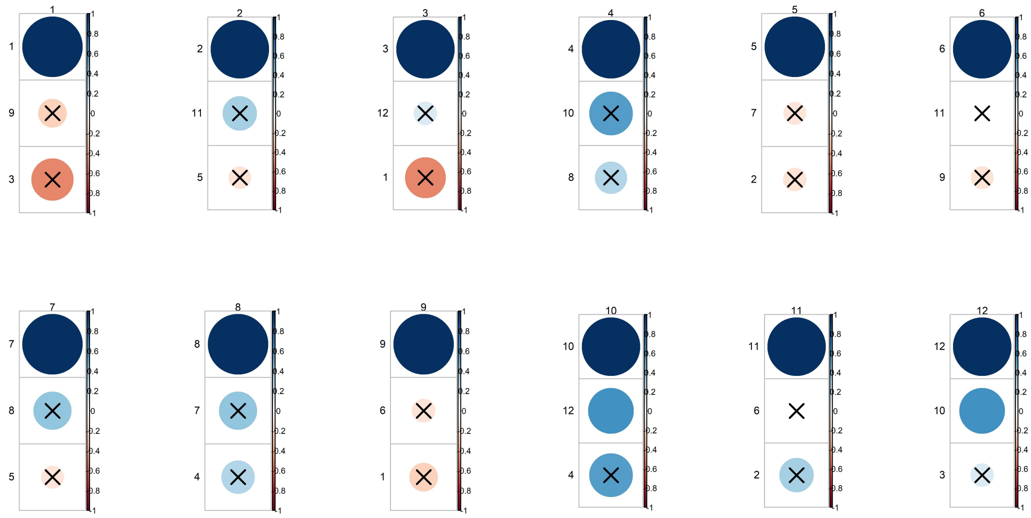
Notes: Displayed distributions incorporate posted prices in all supergames and subgames. Grey highlighted areas correspond to prices of the subgame perfect Nash equilibrium of the static game. Kernel densities are estimated via the Gaussian Kernel function and bandwidth is one standard deviation of the kernel.

Figure C.6: Outsiders' price distributions of non-communication treatments



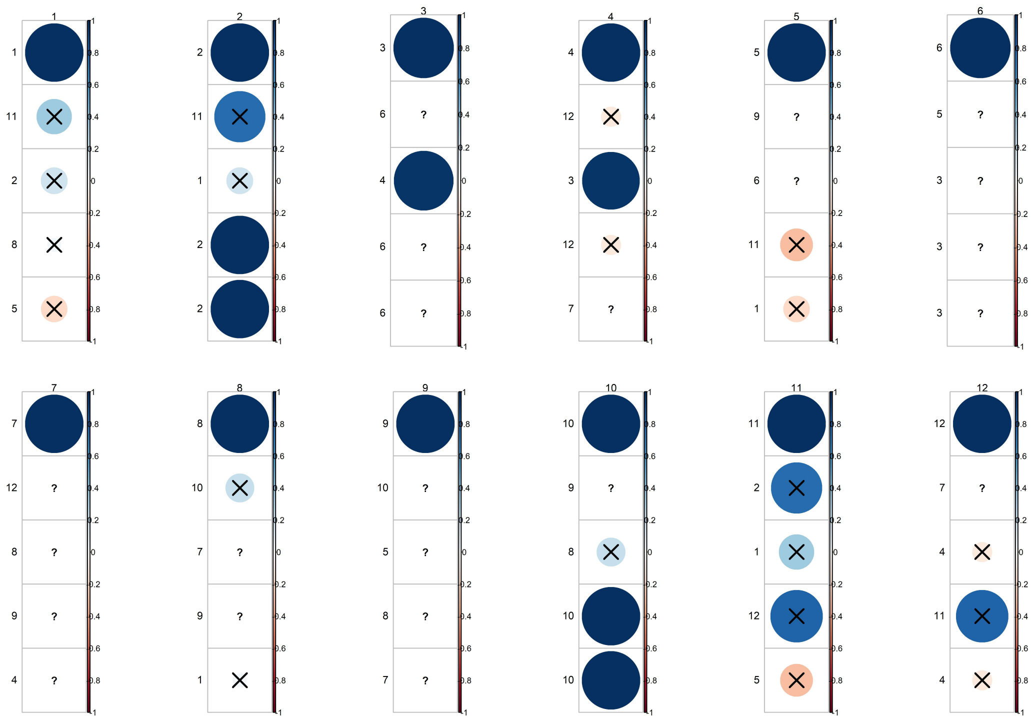
Notes: Displayed distributions incorporate posted prices in all supergames of firms who overpriced in $k = 1$ and consequently served no demand initially. Grey highlighted areas correspond to prices of the subgame perfect Nash equilibrium of the static game. Kernel densities are estimated via the Gaussian Kernel function and bandwidth is one standard deviation of the kernel. N20: 12,12,11 market obs. of monopolization; 8,9,8 market obs. of splits. N0: 12,12,9 market obs. of monopolization; 3,9,8 market obs. of splits.

Figure C.7: Correlation towards prior partner markets in supergame two in N0



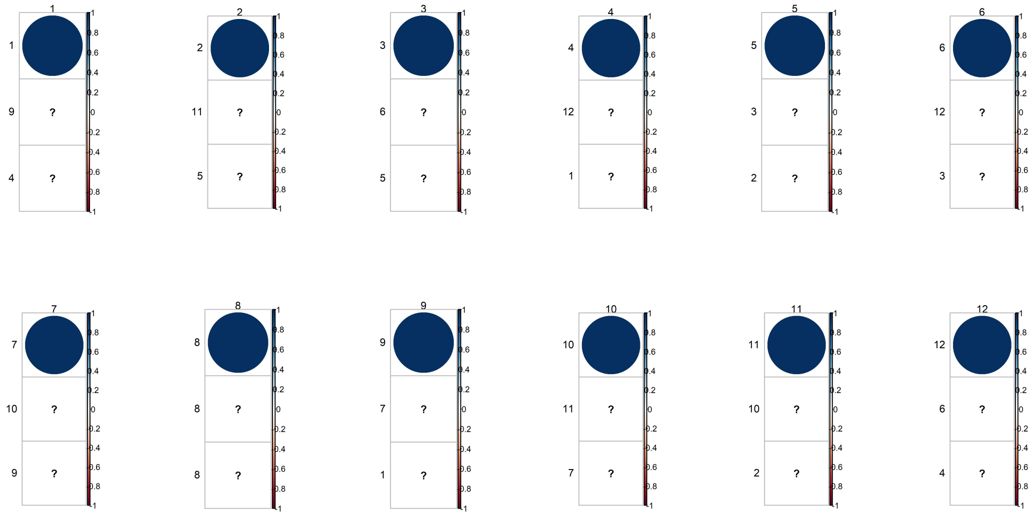
Notes: Correlation coefficients are displayed according to colored scaled points. The size of the dots as well as the color scale refers to the intensity and sign of the correlation. A crossed out dot refers to a correlation coefficient that is not significantly different from zero. The significance level is 0.05. A question mark indicates that the correlation coefficient cannot be computed because at least one of the groups exhibits an invariant price set.

Figure C.8: Correlation towards prior partner markets in supergame three in N0



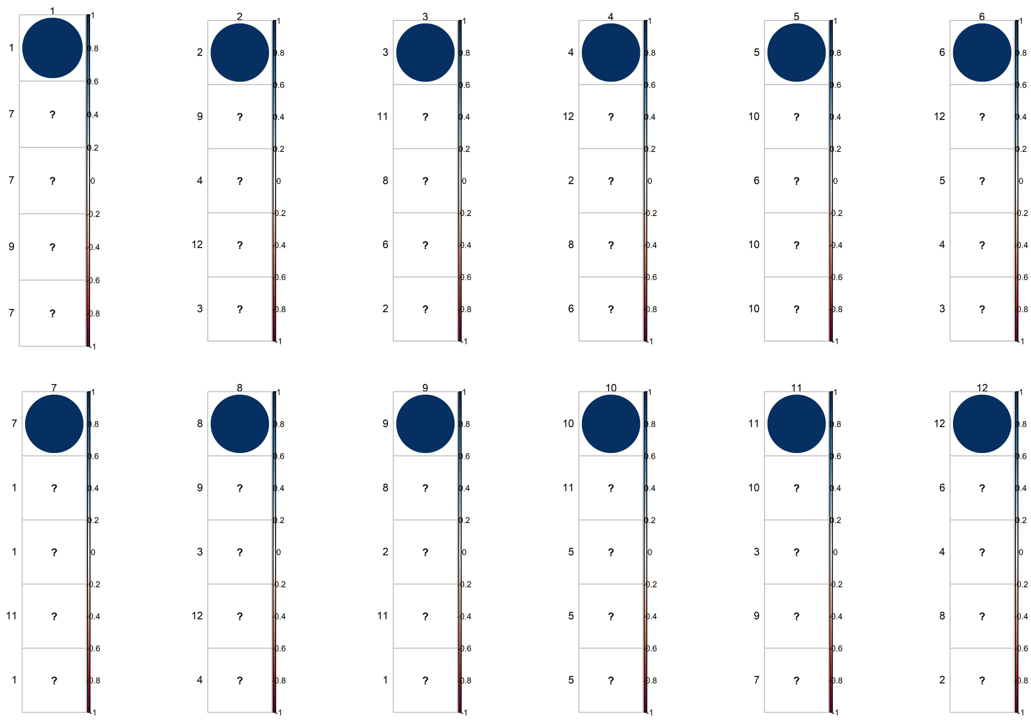
Notes: Correlation coefficients are displayed according to colored scaled points. The size of the dots as well as the color scale refers to the intensity and sign of the correlation. A crossed out dot refers to a correlation coefficient that is not significantly different from zero. The significance level is 0.05. A question mark indicates that the correlation coefficient cannot be computed because at least one of the groups exhibits an invariant price set.

Figure C.9: Correlation towards prior partner markets in supergame two in T20



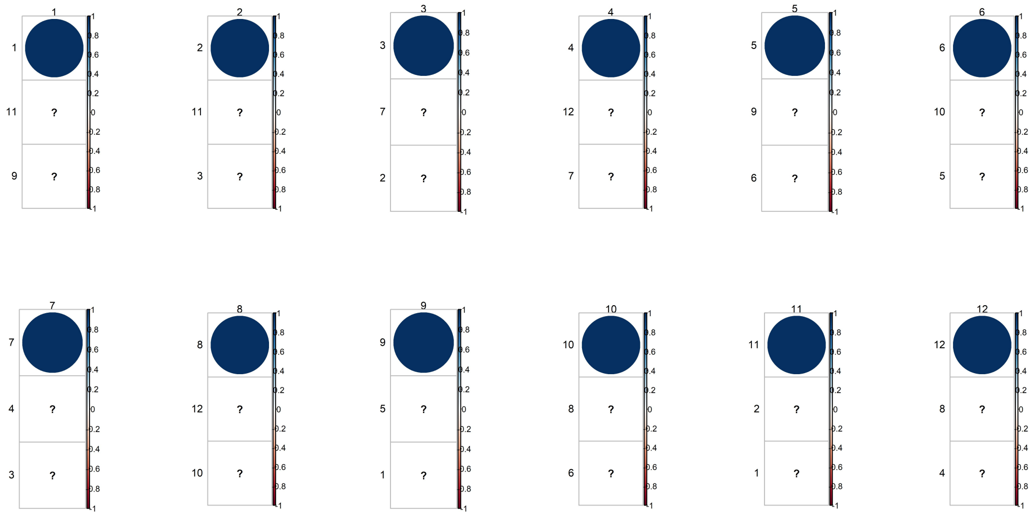
Notes: Correlation coefficients are displayed according to colored scaled points. The size of the dots as well as the color scale refers to the intensity and sign of the correlation. A crossed out dot refers to a correlation coefficient that is not significantly different from zero. The significance level is 0.05. A question mark indicates that the correlation coefficient cannot be computed because at least one of the groups exhibits an invariant price set.

Figure C.10: Correlation towards prior partner markets in supergame three in T20



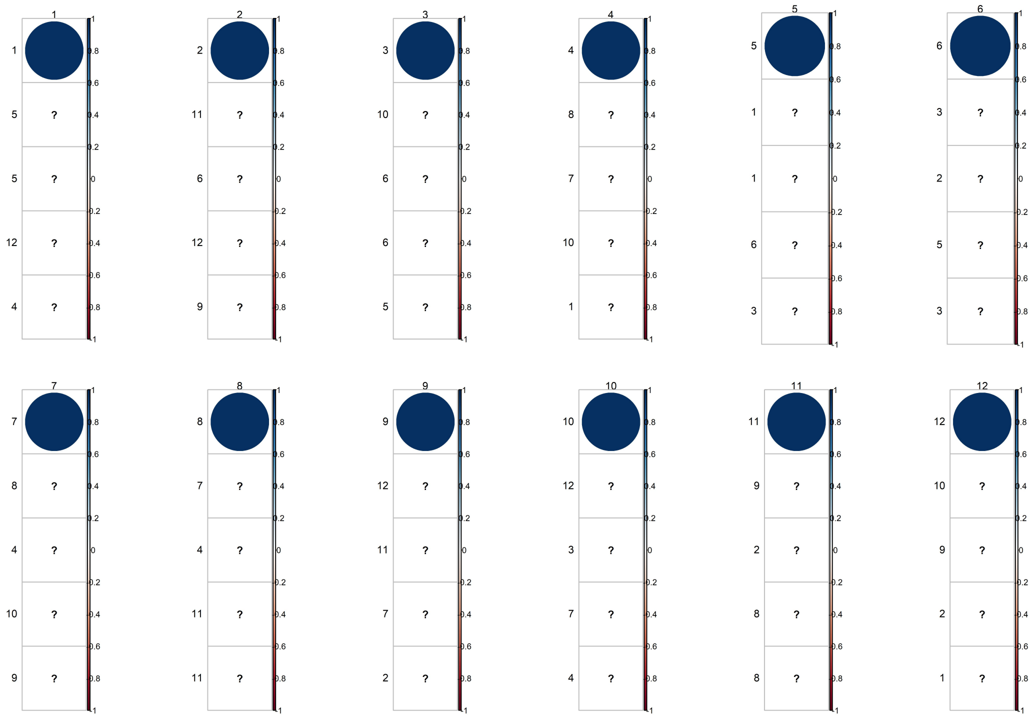
Notes: Correlation coefficients are displayed according to colored scaled points. The size of the dots as well as the color scale refers to the intensity and sign of the correlation. A crossed out dot refers to a correlation coefficient that is not significantly different from zero. The significance level is 0.05. A question mark indicates that the correlation coefficient cannot be computed because at least one of the groups exhibits an invariant price set.

Figure C.11: Correlation towards prior partner markets in supergame two in T0



Notes: Correlation coefficients are displayed according to colored scaled points. The size of the dots as well as the color scale refers to the intensity and sign of the correlation. A crossed out dot refers to a correlation coefficient that is not significantly different from zero. The significance level is 0.05. A question mark indicates that the correlation coefficient cannot be computed because at least one of the groups exhibits an invariant price set.

Figure C.12: Correlation towards prior partner markets in supergame three in T0



Notes: Correlation coefficients are displayed according to colored scaled points. The size of the dots as well as the color scale refers to the intensity and sign of the correlation. A crossed out dot refers to a correlation coefficient that is not significantly different from zero. The significance level is 0.05. A question mark indicates that the correlation coefficient cannot be computed because at least one of the groups exhibits an invariant price set.

Table C.5: Critical discount factors by punishment intensity and deviation timing

	Early deviation ($k=1$)	Late deviation ($k=2$)
Without switching costs ($S=0$)	$\frac{1}{1-\delta}\Pi^{i^{2C}} \geq (p^{max}-c)m$ $\delta_B^{i^1} \geq 0$	$\frac{1}{1-\delta}\Pi^{i^{2C}} \geq \Pi^{i^C} + (p^{max}-c)m$ $\delta_B^{i^2} \geq \frac{1}{3}$
Switching costs (given **Assumption 1**)		
Harsh punishment	$\frac{1}{1-\delta}\Pi^{i^{2C}} \geq [(p^{max}-c)m + S\cdot m]$ $\delta_{SC}^{i^{H,1}} \geq 1 - \frac{p^{max}-c}{p^{max}-c+S}$ $0, \delta_{SC}^{i^{H,2}} < \delta_{SC}^{i^{H,1}} < \frac{1}{3}, \delta_{SC}^{i^{S,1}}$	$\frac{1}{1-\delta}\Pi^{i^{2C}} \geq [\Pi^{i^C} + (p^{max}-S-c)m]$ $\delta_{SC}^{i^{H,2}} \geq 1 - \frac{p^{max}-c}{\frac{3}{2}(p^{max}-c)-S}$ $0 < \delta_{SC}^{i^{H,2}} < \frac{1}{3}, \delta_{SC}^{i^{H,1}}, \delta_{SC}^{i^{S,2}}$
Smooth punishment	$\frac{1}{1-\delta}\Pi^{i^{2C}} \geq [(p^{max}-c)m + S\cdot m]$ $+\frac{\delta}{1-\delta}\left[\left(2\underline{\epsilon}-2c-2S\right)\frac{m}{2}\right]$ $\delta_{SC}^{i^{S,1}} \geq \frac{S}{\left(\frac{p^{max}-c}{2}+S\right)}$ $\frac{1}{3}, \delta_{SC}^{i^{H,1}}, \delta_{SC}^{i^{S,2}} < \delta_{SC}^{i^{S,1}} < \frac{1}{2}$	$\frac{1}{1-\delta}\Pi^{i^{2C}} \geq [\Pi^{i^C} + (p^{max}-S-c)m]$ $+\frac{\delta}{1-\delta}\left[\left(2\underline{\epsilon}-2c-2S\right)\frac{m}{2}\right]$ $\delta_{SC}^{i^{S,2}} \geq \frac{\frac{1}{2}(p^{max}-c)-S}{(p^{max}-c-S)}$ $0, \delta_{SC}^{i^{H,2}} < \delta_{SC}^{i^{S,2}} < \frac{1}{3}, \delta_{SC}^{i^{S,1}}$

Notes: $\Pi^{i^C} = (p^{max}-c)\frac{m}{2}$ is defined as the cartel profit of a single market stage and is identical for competition with and without switching costs. $\Pi^{i^{2C}} = 2\cdot\Pi^{i^C}$ is then the cartel profit of two market stages and an entire playing period. Under "harsh punishment" the smallest competitive equilibrium profit of zero is used as a punishment threat, whereas "smooth punishment" corresponds to the highest competitive equilibrium profit given equation (3.6).

Table C.6: Difference-in-difference estimation

	Dependent variable: *Mean market period profit*		
	SG_1	SG_2	SG_3
Communication $[0,1]$	1,200.42***	1,048.44***	795.75***
	(87.48)	(52.46)	(69.64)
Switching Cost $[0,1]$	35.31	−266.30***	−577.75***
	(87.48)	(52.46)	(69.64)
Communication × Switching Cost	−344.06***	337.86***	561.25***
	(123.71)	(74.18)	(98.48)
Constant	296.67***	654.89***	998.25***
	(61.86)	(37.09)	(49.24)
Observations	288	576	240
Adj. R^2	0.499	0.657	0.695

Notes: Estimated OLS regression coefficients with robust standard errors in parenthesis. The dependent variable is the mean profit of a market in a playing period. *Communication* is a dummy, which takes the value 1 for observations from communication treatments T20 & T0. *Switching Cost* is a dummy, which takes value 1 if observations are from treatments with Switching Costs N20 & T20. *Communication* × *Switching Cost* is an interaction of the previous two dummies. Significance levels of the coefficients are indicated according to *p<0.1; **p<0.05; ***p<0.01.

Table C.7: Firms' mean profits by period and market stage

Profits (Taler /Period) (Taler /Market phase)	Aggregate		Monopolist		Outsider		Splitter	
N20	**380.8**		**714.7**		**3.71**		**439.7**	
	64.08	316.68	161.44	553.22	0	3.71	18.65	421.01
N0	**636.1**		**743.8**		**180.8**		**1189.1**	
	332.9	303.2	496.7	247.1	0	180.8	601.8	587.3
T20	**1622.4**		**1266.7**		**292.7**		**1786.6**	
	819.6	802.8	836.7	430.0	0	292.7	897.8	888.8
T0	**1669.2**		**1608.2**		**1053.0**		**1795.6**	
	842.4	826.8	1376.4	231.8	0	1053.0	899.9	895.7

Notes: Bold values display mean profits of a playing period, plain values refer to mean profits in the respective market stages.

C.6 Experimental instructions

Instructions for T20 treatment (translations from German)

Welcome to the experiment. Please read the following instructions carefully. In this experiment you can earn money dependent on your decisions and that of others. Please remain quiet during the experiment and do not communicate with other participants. Raise your hand in case you have any questions.

In the experiment you represent a company which is in a market with another firm. Over the course of each **game** you are always in the market with the identical firm. Each **game** can consist of multiple **rounds**. After each **round** within a **game**, the **game** continues with a probability of $\frac{7}{8} = 87.5\%$. The probability is constant and identical in each **round**. Whether the **game** continues is determined at the end of each **round** by drawing a random number between 0 and 1. The game continues as long as this random number is smaller than the value of 0.875.

Please note: Expected payoffs of the next **round** depend also on the continuation probability of 87.5%.

Prior to each **game** you are randomly matched to another participant to form a market. Before each **game** starts, you both are able to communicate with each other via chat for 2 minutes. The experiment ends after 3 **games** have been played.

In each **round** you represent a company that manufactures a product at costs of 40 ECU per unit! The market consist of 30 consumers who all want to buy one unit of the good at the cheapest price. Their maximum willingness to pay is 100 ECU and they will not buy a unit of the product at a price above that threshold. Each of the two companies in a market is able to serve all 30 consumers.

Each **round** consists of two stages. **Market stage 1** and **market stage 2**.

In **market stage 1** both firms decide on their selling prices from the continuous set of $[0, ..., 100]$ and the firm with the lowest price sells it's product at this price. In this case the other firm sells to no consumers. If both firms post simultaneously the lowest selling price, consumers' demand is equally split between both firms. Please see the following examples for clarification:

Example 1: Suppose firm 1 chooses a selling price of 85 and firm 2 a selling price of

75. Firm 2 therefore sets the lowest price and sells 30 units at price of 75. Considering the unit costs of 40, firm 2 earns 1050 ECU. Firm 1 sells to no consumers and earns 0 ECU. Calculation of firm 2's payoff: $(75 - 40) \cdot 30 = 1050$.

Example 2: Suppose firm 1 and firm 2 choose both a selling price of 70. Since they both charge the lowest price, consumers' demand is equally split up. Both firms sell 15 units at the chosen price of 70. Both firms earn, again considering unit costs, a payoff of 450 ECU. Calculation of firm 1's & 2's payoff: $(70 - 40) \cdot 15 = 450$.

At the end of **market stage 1** each firm is informed about chosen prices of both firms and its own payoffs. After this, **market stage 2** starts.

In **market stage 2** firms again choose their selling prices. However, consumers got used to the supplier's product which they bought previously. For the purchasing decision in market stage 2 they therefore tend to buy the product from their initial supplier at which they have already bought before in market stage 1. Consumers face switching costs of 20 ECU in case they switch to the product of the other firm. Hence, consumers only switch if the price of the other firm is attractive such that it compensates the consumers for the incurred switching costs. If consumers are indifferent between buying again at the same firm or switching to the other (selling prices plus switching costs are identical to consumers), demand of those indifferent consumers is equally split up between both firms. Please see the following examples for clarification:

Example 3a: Suppose all consumers bought the product of firm 1 in market stage 1. In market stage 2 firm 1 chooses a selling price of 75 and firm 2 of 60. For the consumers it is cheapest to buy again at firm 1 since they would face a selling price of 60 and switching costs of 20 in case they switch to firm 2. Firm 1 therefore sells 30 units at a price of 75 and earns, considering unit costs, a payoff of 1050 ECU. Calculation of consumers' purchasing decision:
$Price\ of firm\ 1 < Price\ of\ firm\ 2 + Switching\ costs\,;\ 75 < 60 + 20.$

Example 3b: Suppose all consumers bought the product of firm 1 in market stage 1. In market stage 2 firm 1 chooses a selling price of 75 and firm 2 of 50. For the consumers it is now cheapest to switch to the product of firm 2 despite the switching costs. Calculation of consumers' purchasing decision: $75 > 50 + 20$.

Example 3c: Suppose all consumers bought the product of firm 1 in market stage 1. In market stage 2 firm 1 chooses a selling price of 75 and firm 2 of 55. From the consumers' point of view both firms charge the cheapest price. In this case consumers are indifferent and their demand is split up equally. Calculation of consumers' purchasing decision: $75 = 55 + 20$. Payoff calculation: firm 1 $(75 - 40) \cdot 15 = 525$; firm 2 $(55 - 40) \cdot 15 = 225$.

Example 4: Suppose consumers' demand has been equally split in market stage 1 (see Example 2). In market stage 2 firm 1 chooses a selling price of 75 and firm 2 of 60. For the customers of both firms it is cheapest to buy again at the same firm as in market stage 1. Calculation of consumers' purchasing decision: firm 1 customers stay because of $75 < 60 + 20$; firm 2 customers stay because of $75 + 20 > 60$.

At the end of market stage 2 each firm is informed about chosen prices of both firms and its own payoffs. In addition to this you have access to a profit calculator for your pricing decision.

You will earn money based on your cumulative earnings in the experiment at an exchange rate of:

$$1\ EUR = 3000\ ECU$$

Additionally you are endowed with an income of 4 EUR. If you incur a loss, this will be set off against your initial income. Before the experiment starts please answer the introductory questions which will be displayed on your screen in a moment. The correct answers will be given after this.

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Conclusion

This thesis analyzes competition, or the lack thereof, on digital markets. It forges a bridge from the provision of network infrastructure to resulting inefficiencies and potential threats to competition. It makes contributions in the field of digital economics while employing three different methodologies of research: Theory, empirics and experiments.

Chapter 1 investigates the inter-technology competition of three network architectures, that is, VDSL-Vectoring, TV-Cable and fiber-optics. In doing so, it originally examines a technologically restrictive deployment environment which rules out the use of Vectoring but is nevertheless found to be ineffective in promoting fiber deployment. Locally targeted subsidies are more effective in achieving this.

Chapter 2 generalizes, among others, a monopolist's provision of network coverage in a theoretical framework of horizontal differentiation. The theoretical model departs from two common assumptions in the literature. First, consumer preferences follow more realistically a log-concave density function which also includes the commonly used uniform distribution. Secondly, the product is represented by an interval instead of a point and thus can be customized to perfectly match a variety of consumer preferences rather than one single characteristic. In this setting the chapter finds a novel inefficiency in the underprovision of product characteristics.

The in-depth customization of products often gives rise to consumer switching costs which are the subject of Chapter 3. While switching costs theoretically induce "invest and harvest" behavior of firms, the aggregate effect on prices, the competitiveness of markets and the incentives to collude are rather unclear. The chapter finds that in an experimental setting the "investment" pressure dominates the "harvesting" motive. Further, consumer switching costs increase the monetary gains from colluding explicitly an thus make such agreements more lucrative.