Empirical Essays on the Role of Location and Distance in Economics

D I S S E R T A T I O N

zur Erlangung des akademischen Grades

Doctor Rerum Politicarum (Dr. rer. pol.)

im Fach Volkswirtschaftslehre

eingereicht an der Wirtschaftswissenschaftlichen Fakultät
Heinrich-Heine-Universität Düsseldorf

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Abgabedatum:	21.12.2020

Acknowledgements

I would like to take this opportunity and express my profound gratitude to everyone who has aided me throughout the travails of writing this thesis.

This dissertation was written during my employment at Heinrich-Heine-Universität (HHU) and the Düsseldorf Institute for Competition Economics (DICE) as *Wissenschaftlicher Mitarbeiter* and I am thankful for the opportunity provided to me by these institutions. In particular, I want to thank my supervisor Justus Haucap for his support over the years. Crucially, he granted me academic freedom and liberty, encouraging and enabling me to pursue my research interests and accomplish this thesis. I am also grateful to Joel Stiebale for agreeing to be the co-supervisor of this thesis.

Moreover, gratitude is due to my co-authors Niklas Fourberg and Nico Steffen for our joint work.

I thank Andreas Kokot for a myriad of discussions about my thesis, his thesis and everything. The recurring discussions with Amrei Stammann, Daniel Czarnowske, Till Krüger, Max Osterhaus and Theresa Schmitz on research and teaching in statistics and econometrics have been invaluable as well. Additionally, I would like to thank my colleagues from the HHU's CM team as well as Max Horst and Christina Heldman for their general camaraderie. Beyond that, I have appreciated the informative discussions with professors and colleagues at DICE and HHU.

Lastly, but vitally: Meine Dankbarkeit gilt meiner Familie und meinen Freunden. Sie gilt Michael für die Möglichkeit zu studieren, Ina und Marianne für eine Zuflucht am Waldrand. Sie gilt Brigitte für den freien Platz am Tisch. Sie gilt Stella für einen ewigen Sommer. Sie gilt Martin und Uwe für jedes frühe Aufstehen und den Weg hinaus. Sie gilt Hendrik für abendliche Diskussionen über Fiktion und Wirklichkeit. Sie gilt Kathrin für ein teils geteiltes Schicksal.

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Chapter 1

Introduction

Economic activity inevitably revolves around the locations of its players and their efforts in overcoming the existing distances between them. The nature and structure of these choices and obstacles have changed over time through the advent of new technologies, social changes and cultural progress, but its fundamental questions remain the same: How can distance be overcome to facilitate interaction, either as matching buyers and sellers or as enabling sellers to compete for buyers?

For each party engaged in economic activity, this question translates to different concerns. Consumers and producers have to consider their choices of location and their willingnesses to exert effort in accessing more remote market participants. Regulators on the other hand have to construct legislation, international coordination and infrastructure to reduce the costs of those efforts and to alleviate the uncertainties arising from these costs and differences.

These considerations likewise need to account for the different types of interaction: Communication, transportation and negotiation. The former decides on the ability to engage with other players, be they consumers, competitors, producers or regulating state agencies. Transportation then decides on the ability to actually exchange goods and non-remote services, whereas negotiations, lastly, decide on whether any exchange or contract can be agreed upon.

This thesis aims to provide an insight into these interactions, structures and their governance. To this end, exemplary cases for the contemporary forms of the interaction types are presented and analysed to assess their scope, the underlying mechanisms and the regulatory measures applied to them.

Chapter 2, entitled **Fiber vs. Vectoring: Limiting Technology Choices in Broadband Expansion** (co-authored by Niklas Fourberg and published in *Telecommunications Policy*) addresses the topic of communication. It deals with the modernisation of an ageing telecommunications infrastructure and the regulatory actions designed to accelerate that process. Specifically, it analyses the structural determinants of fiber optics deployment in Germany, measuring also the role of technology competition from the existing infrastructures and the impact of regulation. Germany is well-suited for this analysis due to its dense copper-based legacy network, currently used for the VDSL-Vectoring bridge technology, and its parallel TV-Cable network, which provides a high-speed capable competitor. Thus, local characteristics and their impact on fiber optics deployment can be analysed alongside competition concerns relating to high up-front investment costs. In addition, a technologically-restrictive deployment policy - as proposed by the European Commission - is evaluated utilising a natural experiment within the German market which had restricted Vectoring deployment.

The analysis uses German micro-data on the municipality level and investigates both the extensive and intensive margins of investment into fiber optics. Its results highlight the importance of location for infrastructure deployment decisions and extent: The more secluded or remote a municipality is, the lesser is its chance of receiving an infrastructure upgrade. On the other hand, proximity to a municipality with fiber deployment raises these chances, as does construction of new residential housing, which is accessed with fiber optics by default. Regulation can alter these odds by providing subsidies for fiber optics deployment specifically earmarked for projects on the municipal level. These are found to be highly effective, increasing deployment likelihoods by three to four percentage points for every 100.000 Euro spent. By contrast, a passive technologically-restrictive regulation has no discernible impact. Lastly, existing competing networks appear beneficial to fiber optics deployment, signalling attractive locations. But their expansion appears to curtail profitability of fiber expansion, reducing the intensity of its deployment.

From the perspective of regional economics, these results hold several implications. First, modern communications technologies may be able to connect people across vast distances, but their deployment and availability are still shaped by the people's locations. There, those who are more distant and remote in a geographical sense are again in the disadvantage. Secondly, government agencies can alleviate these disadvantages but might be required to provide incentives instead of simply restricting the use of undesired technologies and outcomes.

Chapter 3, entitled **Competition on the Fast Lane - The Price Structure of Homogeneous Retail Gasoline Stations**, switches to the topics of transportation and road infrastructure. It addresses the costs of transportation for both cargo and passengers by analysing the price structure and mechanisms of a homogeneous group of retail gasoline stations. They are located directly on Germany's *Autobahn* motorway network, which is one of the densest and most intensively used networks in the world; not least because of Germany's central location within Europe. These *Autobahn* fuel stations have a number of desirable characteristics for the analysis. They are highly regulated, mandating conformity and thus homogeneity across all stations. They are accessible only from the *Autobahn* for which detailed traffic data exists, permitting the use of said traffic as a proxy for demand. And they are relevant for truck traffic - i.e. logistics - as they provide sanitary services, refuelling and rest opportunities.

Using hourly data for the prices of more than 300 *Autobahn* fuel stations and adjacent traffic for all of 2018, the analysis comes to reassuring results. The observed relationships match the Edgeworth cycling behaviour commonly assumed for gasoline retail and link the undercutting behaviour observed in these cycles to increases in potential demand. Cycling in general and price reductions - the aforementioned undercutting - in particular become more likely as traffic increases, implying stronger competition in periods of higher demand.

From this perspective, the costs of travel and transportation would decrease with its density and volume, so long as meaningful competition exists. Notably, this pressure depends on the location of competing stations. *Autobahn* stations can sustain a significant price premium due to their own, privileged position on the *Autobahn* network, but nonetheless need to account for the presence of *Autohof*-type stations, which are similar in characteristics and located just outside their network. While this reveals the impact of location - and the long-term effects of network design decisions -, it also suggests a means of alleviating the issue by expanding or integrating infrastructure networks.

Finally, chapter 4, entitled **Economic Preferences and Trade Outcomes** (co-authored by Nico Steffen), assumes an international perspective and analyses the impact of population preference characteristics on negotiations and, by that channel, trade outcomes. This study addresses both physical and personal distance as determinants of international cooperation and economic exchange. To this end, bilateral, goods-category specific trade volumes are viewed as the aggregate result of bilateral negotiations between agents of the given country pair. These negotiation outcomes reflect the players' efforts to achieve a result suitable to their desired product mix, which is affected by their economic preferences. These preferences are time, risk and reciprocity attitudes. The former two refer to the willingness to engage in long-term commitments and avoid risks, respectively, while reciprocity is split into positive (e.g. rewarding gifts) and negative (e.g. costly punishment) forms. All four of them are taken from the Global Preference Survey and linked to trade outcomes via unilateral and bilateral parameters in a gravity framework.

The analysis finds a significant impact by these preferences on trade flows and bilateral relationships, both on the country-level and between bilateral partners. Countries differing in their willingness to behave negatively reciprocal tend to trade significantly less amongst each other. This can be attributed to the destabilizing effect of unexpected punishments faced by the less negatively reciprocal partner. Differences in positive reciprocity on the other hand intensify trade relationships, likely due to a stabilising effect of unexpected rewards by the more positively reciprocal partner. Patient or risk-averse countries tend to shift towards exporting more differentiated goods as opposed to homogeneous goods and vice versa. These observations can be explained by a self-selection of the involved players into the production of goods fitting their personal preferences, if given the chance. In essence, they perform a kind of term and risk transformation.

By these effects, it can be observed that soft, behaviourally-motivated distances between nations and their players can affect economic outcomes via mechanisms both similar, but also markedly different from physical distances. Thus, these relationships might constitute a different source of distance between economic agents than the physical one.

Chapter 2

Fiber vs. Vectoring: Limiting Technology Choices in Broadband Expansion

Co-authored with Niklas Fourberg

2.1 Introduction

Communication networks are not only the backbone of today's digital era economy but are also shaping 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, 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) employ exclusively legacy copper double-wires on the local loop ("last mile") or rely on the hybrid-fiber-coaxial (HFC/TV-Cable) technology. Such existing technologies are readily available and less costly to roll out. This, naturally, affects network operators' calculations 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) justifies this restriction by stating 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. Indeed, influences on FttP deployment in particular have not been thoroughly explored, be it regarding structural drivers or effects resulting from infrastructure competition. We aim to close this gap.

This paper 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 drivers of FttP deployment at the

[1] Cisco (2017) estimates the data traffic over fixed internet 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).

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. For examining effects of a technologically restrictive deployment regulation, a situation deemed favorable by the EC, we exploit a natural experiment in the German telecommunications market from December 2013 to June 2017. 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, conform with the new EC mandate, 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 FttP deployment and the deployment 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 one at the intensive margin. Hence, Vectoring might signal deployment-worthy municipalities but simultaneously acts as a substitute once both networks coexist, adversely affecting 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 in a municipality as part of the Bavarian subsidy program is associated with an increased likelihood of fiber deployment by three to four percentage points.

The remainder of the paper is structured as follows. Section 2.2 provides literature findings on the main strands to which we contribute. Section 2.3 comments on Germany's infrastructure landscape and defines our identification. Section 2.4 elaborates on the data used in our analyses. Section 2.5 introduces the empirical strategy whose results are presented in Section 2.6. Finally, the paper concludes in Section 2.7.

2.2 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 the options for policy makers 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 as an instrument to steer the physical deployment of telecommunications infrastructure. Hence, our paper is a first step in assessing the consequences of such a scheme.

The most common and most widely studied regulatory 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 improve 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

[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.

fiber deployment. Briglauer (2019) himself provides support for this perspective by observing broadband coverage to increase by 18.4 to 25 % 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, Bouckaert *et al.*, 2010, Distaso *et al.*, 2006, Höffler, 2007, 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-platform 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 the 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.

Additionally, Calzada *et al.* (2018) study indeed the deployment of FttH in Spain but only projects carried out by the incumbent firm Telefonica. Their assessment of inter-technology competition with respect to Vectoring is based on Bitstream unbundling, the Vectoring based wholesale product. However, this approach implies a negative strategic bias since both FttH and the legacy infrastructure are operated and monetized by the incumbent. Thus, the incumbent's deployment incentives of FttH are systematically limited in areas where Vectoring coverage is high. Our study improves on this in considering firm-independent infrastructure deployments and, therefore, is a first step in understanding the interdependencies between three distinct competing infrastructures and the deployment of FttP.

2.3 Broadband Infrastructure in Germany & Identification

In this section, we compare the German network landscape to the regulatory demands placed upon it. The EC postulated 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 upon the technological peculiarities of the historic public switched telephone network (PSTN).

2.3.1 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% of municipalities had been accessed by December 2013. The geographical deployment pattern is displayed in Panel A of Figure 2.1. 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 maximum downlink of up to 1.5 Gbit/s and uplink of 200 Mbit/s, the latter was introduced in 2013 and permits a maximum 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]

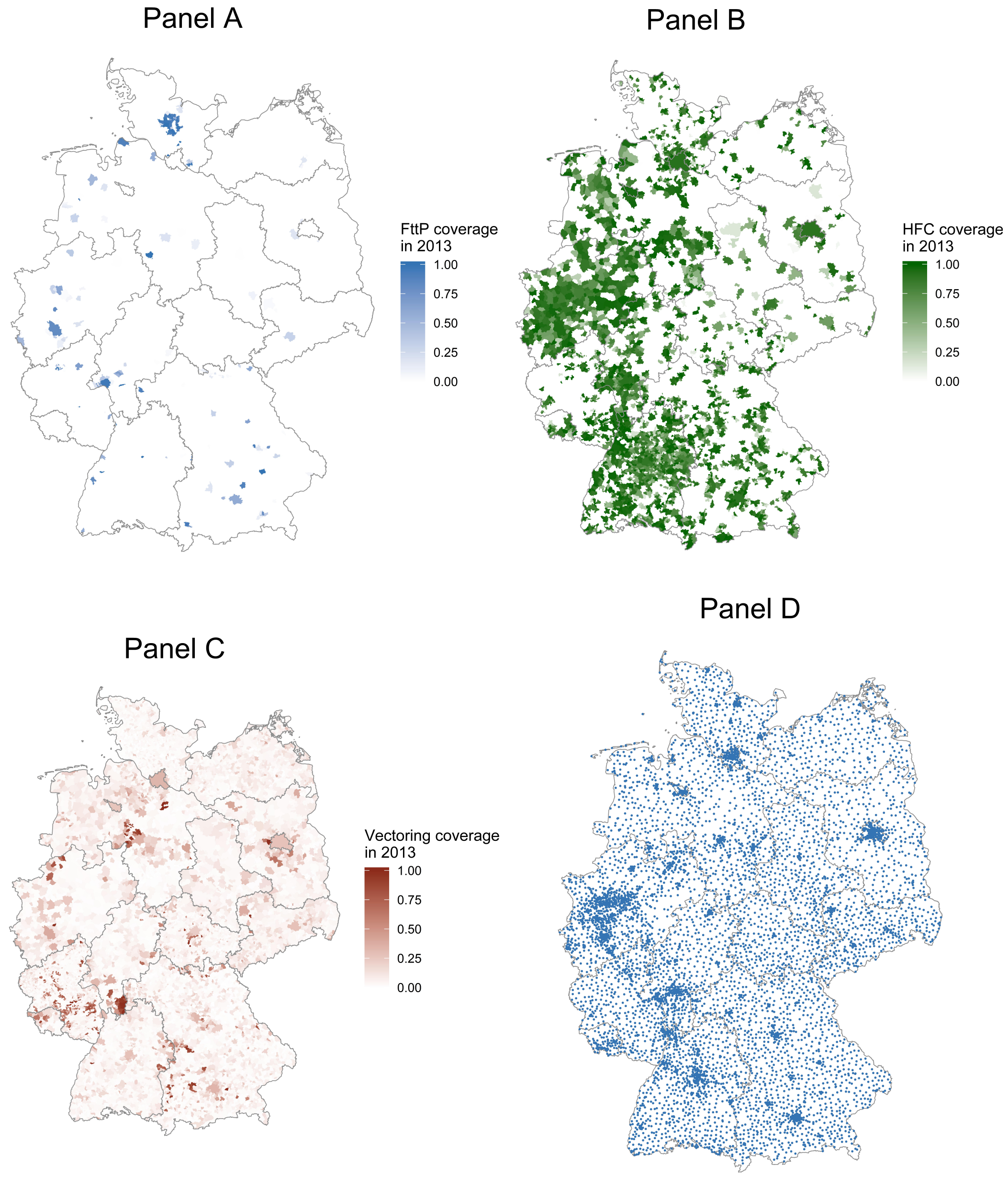
Deployment or expansion costs are moderate as most of the legacy CATV wiring can be re-used and only the equipment installed in network nodes needs to be replaced. However, the network covers only approximately 70% of all German households and by December 2013 only 27.77% of German municipalities had access to a high-speed HFC connection (see Panel B of Figure 2.1 for the geographical deployment pattern).

The last and 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

[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 2.1: 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.

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% 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 based access technology cannot offer a reliable and widespread upgrade potential towards gigabit speeds. 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 % of German municipalities were connected by a VDSL based technology offering 50 Mbit/s downlink or more (Vectoring). Panel C of Figure 2.1, once again, displays the geographical deployment pattern.

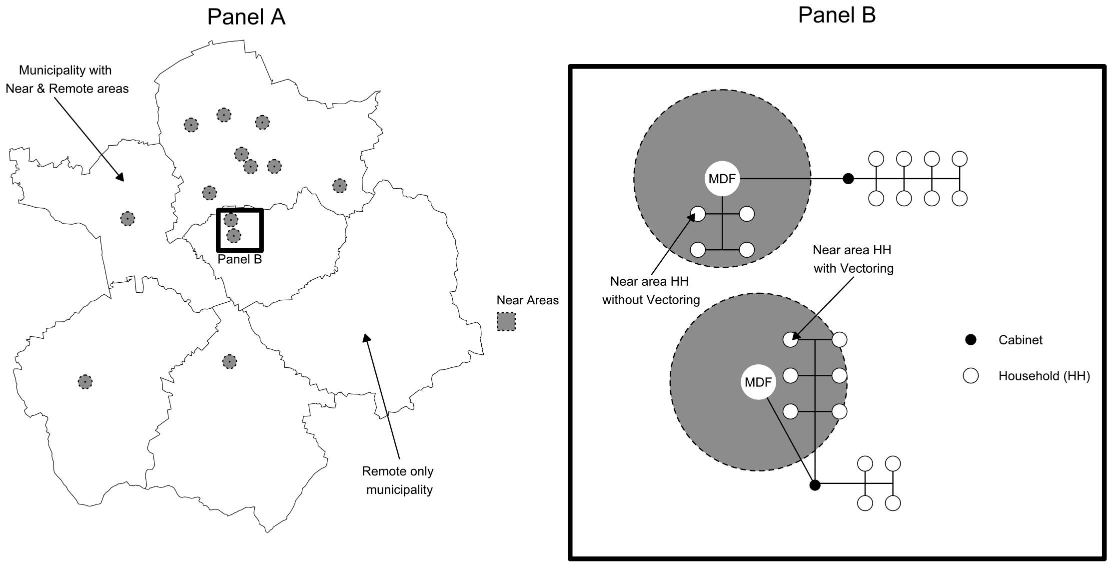
2.3.2 Identification

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 inoperable 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

[7]Specifically, this 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.

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 2.2 illustrates the classification of *Near*- and *Remote*-areas within municipalities based on MDF placement.

Figure 2.2: 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.

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. The technical limitations apply to wiring length, not aerial distance, but wiring may follow street corners or 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 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 2.2 displays the schematic structure of the local loop and the special case mentioned above.

The placement of MDFs 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 MDFs

[8]Furthermore, choosing a radius other than the 550 meters that define the technological limitation would be arbitrary. Only by specifically observing and accounting for wire length could accuracy be improved but this data is not accessible.

grew with population size and remained substantially smaller in the GDR. Notably, wiring length had no impact on the quality of telephone services, allowing MDF location choices to be based on structural characteristics and the technological restrictions of the time.[9] MDFs 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 less MDFs or even none at all, shifting the location choice to questions of lots, suitable buildings and topographic issues. Panel D of Figure 2.1 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 prior to estimating a treatment effect. 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.[11] In conclusion, we chose to augment the identification by conducting a propensity score matching based on the variables best predicting MDF placement (see Section 2.5.2).

2.4 The Data

The data we use describe a network operator's deployment decision for a given municipality along four dimensions which we capture in separate variable categories. Technology (T) contains all variables concerning broadband infrastructure. Variables in the market size (Y) category capture relevant influences from the demand side, while accessibility (X) contains deployment cost indicators. All funding related variables are part of the subsidy (S) category. Finally, federal state (*Länder*) fixed effects (L) account for unobserved differences between German federal states. These could be rooted in the structures of local markets or different construction regulations. They also capture intangible factors such as differences in state-level policy and laws or broader trends stemming from the German separation. In what follows we comment on the data sources and the inclusion of a specific variable in a given category.

2.4.1 Broadband Data

Infrastructure data is sourced from the *Breitbandatlas*, a database funded by Germany's federal government collecting information on household access to broadband

[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.

[11] Although the decline of coal and steel in the Ruhr valley suggests limitations to persistence in firm agglomeration.

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.[12] The operators' offers are accumulated into a total share of 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 granular aggregation level available is the municipality, providing about 11,000 observational units for Germany.

For identification of the Vectoring-specific regulation (see Section 2.3.2), 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 MDFs within their boundaries and thus have *Near*- and *Remote*-areas, whereas 6211 do not and are thus classified as *Remote*-only. A further four municipalities are small enough to not surpass their respective *Near*-area boundaries. The average network coverages for each municipality type are summarized in Table 2.1.

The main specification includes network coverages in 2013 as well as the coverage increase of all three technologies during the observational period. This is equally motivated by our research goal of investigating technology competition as well as literature findings of Bourreau *et al.* (2018) and Calzada *et al.* (2018) who show that deployment and adoption of fiber is crucially impacted by competing infrastructures. Another technology related variable we consider is a municipality's proximity to already existing FttP deployments in 2013. This dummy variable *nearby10k* captures potential spillover effects from these early accessed municipalities to adjacent ones. It takes the value 1 if the centroid of any municipality with FttP deployment in 2013 is at most ten kilometers distant from its own centroid. These variables together with information on MDF distribution define the technology category (T). Summary statistics for all variables contained in T are presented in Table 2.23 in the Appendix.

The three and a half years covered in the treatment period are sufficient to accommodate for 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 municipalities exhibit, on average, 56% coverage of their households, while municipalities with MDFs receive coverage of around 21% by December 2017.[14] For the whole of Germany,

[12]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*.

[13]The slow expansion of FttP coverage, the most costly and time-consuming technology to roll-out, underlines this assumption (see Table 2.1).

[14]Note that median values for expansion in *Near* & *Remote* municipalities are substantially smaller, at 5% and 6% 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 not improve results since that measure suffers from the reverse: it allows no inference on the intensity of expansion within the constraints of the given municipality, while coverage change does. Moreover, coverage is the

Table 2.1: Average coverages by technologies

Municipality	Count	Fiber.13	Fiber.17	HFC.13	HFC.17	Vec.13	Vec.17
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
Near & *Remote*: *Near*	637	0.0588	0.2174	0.5536	0.5994	0.0967	0.3943
Near & *Remote*: *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 prefixed with *Both* and listed separately with respect to *Near*- and *Remote*-areas. The second part of the table shows the average coverages for all municipalities with positive FttP expansion in the observation period.

average coverage drops to 5.7% and 2.7% percent, respectively. 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.

2.4.2 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.

Market size characteristics (Y) include a municipality's population, the amount of residential buildings (Houses), the average age and the average income per capita of its citizens. These variables are known to determine the attractiveness of a municipality in terms of willingness to pay or sales potential for FttP based services (see Bourreau *et al.*, 2018, Briglauer *et al.*, 2019, Calzada *et al.*, 2018). Generally, wealthier people can more easily afford price premiums for higher bandwidths and younger people are on average more interested in data-intensive services. Table 2.2 presents summary statistics for all variables contained in Y.

The set of accessibility (X) variables covers cost drivers for expansion projects. Apart from the prime factor of population density, which is usually found to exert a positive influence on infrastructure deployment in the literature (Bourreau *et al.*, 2018, Calzada *et al.*, 2018), the main specifications also include a municipality's area, the

policy-relevant measure.

Table 2.2: Summary statistics for market size (Y) variables

Variable	Count	Mean	Median	St. Dev.	Min	Max
Houses	10,956	1,672	556	5,833	0	316,047
Population	10,957	0.731	0.171	4.714	0	342.18
Age	10,940	44.39	44.15	2.490	32.61	58.89
Income p capita	10,945	34.38	33.72	7.144	7.97	142.89

Notes: Summary statistics for all variables contained in the market size (Y) category. The complete list of information on all used variables including their scale of measurement can be found in Table 2.24.

share of newly built houses as well as a ruggedness measure for terrain characteristics and the driving distance (Min_MZ) to the next mid-sized town. New housing is included as these houses will be connected to the existing network via FttP which could induce spillover effects for the deployment of other, already existing houses. Additionally, larger and topographically more uneven municipalities should be more costly to access given the required ductwork. The distance to the next mid-sized town indicates the seclusion of a specific municipality which we expect to raise costs and negatively influence infrastructure deployment.[15]

Related accessibility measures which we consider in robustness specifications include the number of single-family houses, the driving distance to the nearest motorway access and forest as well as industrial areas of a given municipality. Single homes could indicate higher access costs per household due to more ductwork being necessary, whereas larger industrial areas might cause positive spillover effects if they were to be accessed. Forest area and the distance to a motorway access are considered as alternative seclusion indicators to Min_MZ. Lastly, we implement also the number of main distribution frames ($HVT.count$) from category T in a robustness specification. Since MDFs are already accessed with fiber, this can also be interpreted as a cost relevant indicator addressing lower wiring expenses for FttP if MDFs are available in large numbers.

German municipalities (*Gemeinden*) provide information on these variables in the *Regionalstatistik*
database. Data for 2013 is used to align with the start of the observational period, whereupon expansion decisions would have been based.[16] The distance based seclusion measures (Min_MZ, Min_A) are sourced from the *INKAR* database and the topographic ruggedness is calculated from the 30 arc-seconds terrain grid provided by Nunn and Puga (2012).[17] Summary statistics for all variables in X are presented in

[15]The distance measure (Min_MZ) has also been used by Briglauer *et al.* (2019), but was not significant for the set used in their study on the provision of broadband coverage.

[16]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 these 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 FttP expansion.

[17]See http://www.inkar.de/ for the *INKAR* database and https://diegopuga.org/data/rugged/ for the raw data on *Ruggedness* of Nunn and Puga (2012). We are especially thankful to an anonymous reviewer who recommended the inclusion of a ruggedness indicator which improved the quality of our

Table 2.3.

Table 2.3: Summary statistics for accessibility (X) variables

Variable	Count	Mean	Median	St. Dev.	Min	Max
Density	10,946	1.829	0.929	2.765	0	45.312
Single-Family Houses	10,937	0.748	0.763	0.100	0.320	1.000
New Construction	8,436	0.023	0.019	0.018	0.001	0.494
Area	10,948	31.756	18.645	40.099	0.450	891.700
Forest Area	10,948	9.539	4.270	15.620	0	354.030
Industrial Area	10,948	0.301	0.060	1.027	0	41.840
Ruggedness	11,175	0.683	0.548	0.668	0	7.901
Min_MZ	11,021	12.134	11.450	8.666	0	147.346
Min_A	11,021	15.662	12.734	12.477	0	149.665

Notes: Summary statistics for all variables contained in the accessibility (X) category. The complete list of information on all used variables including their scale of measurement can be found in Table 2.24.

2.4.3 Subsidies & Bavaria

Data on subsidies for broadband expansion issued by the federal state of Bavaria are used to measure the impact of direct government aid on FttP deployment; as are the subsidies issued by the federal government itself.[18] The latter were often spread out across entire administrative districts and skewed towards more populated regions.[19] 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 is directed towards less populated, more rural municipalities and is consistently assigned to the specific municipality that applied for it. For a comparison between federal and Bavarian funding choices, see Table 2.4. 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 and was also used by Briglauer *et al.* (2019) for their analysis. The specification of technology in particular 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 planning and construction cycles, we only consider deployment projects that had been approved by the end of 2015. Consequently, we contain the variable *Funding until 15* as the accumulated fiber-specific subsidies a municipality received up to 2015 along with a dummy variable of receiving funding in the subsidy category (S). Figure 2.3 displays the geographical distribution of the funding associated with this selection of projects.

results.

[18] Specifically, by the Ministry of Transport and Digital Infrastructure.

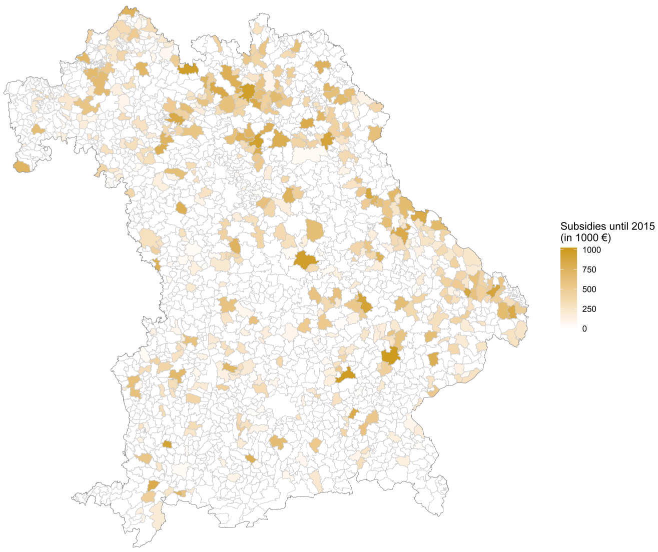
[19] In these cases, when subsidies were allotted to entire districts, the total amount of subsidies was assigned to the corresponding municipalities according to their population- or area-weighted shares. Due to the inherent inaccuracy of this procedure, federal subsidies were also filtered to include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

Table 2.4: 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 until 2015 and specifically including FttP deployment.

Figure 2.3: 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.

2.5 The Model

The empirical strategy addresses, in turn, our three research questions regarding FttP expansion. First, where does it occur? Second, to which extent? And, third, how does 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, for example, deployment costs and existing legacy networks. After identifying these structural determinants, we assess two policy interventions in the form of technology restrictions and subsidies. The methods and models used for this process are explained here.

2.5.1 FttP Expansion

Extensive Margin FttP deployment at the extensive margin is defined as a municipality's probability of 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.[20]

To this end, operators' decision-making on whether to access a municipality or to expand an existing network is based on the four categories of variables defined in Section 2.4: Technology (T), market size (Y), accessibility (X) and subsidies (S) while also accounting for federal state (*Länder*) fixed effects (L). These capture, in order, technology-competition, the commercial attractiveness, the access costs, financial support and state-specific market structures and policy for a given municipality. The fixed effects also account for Germany's economic North-South and East-West differences.

The category-specific subsets of characteristics used in the extensive margin equation are indexed with E. They jointly constitute the set of explanatory variables in the following Logit model on the binary deployment decision for each municipality, which is also estimated linearly.[21]

$$Prob(\text{InvF} = 1|X_E, Y_E, T_E, S, L) = f\left(X_E'\alpha_E, Y_E'\beta_E, T_E'\gamma_E, S'\delta_E, L'\zeta_E\right) \tag{2.1}$$

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 end: Δ FttP $= FttP.17 - FttP.13$.[22] Given that a municipality sees FttP investment, this measure accurately captures the intensity of this resulting deployment.

[20] In fact, it specifically indicates a municipality's "resistance to investment", which decreases as the probability of expansion increases.

[21] 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 2.6.1, 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.

[22] As with the extensive margin specification, the analysis is restricted to first-time FttP investments (see Section 2.6.1). 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.

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 likely irrelevant to the deployment extent, but important to the binary deployment decision - 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:

$$\Delta \text{ FttP} = X_I \alpha_I + Y_I \beta_I + T_I \gamma_I + L \zeta_I + u \quad . \tag{2.2}$$

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. The term 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:

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

2.5.2 Policy Interventions

Technology Regulation As elaborated in Section 2.3.2, 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 in aggregation 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 outside *Near*-areas ($1 - \kappa$). Treated are those municipalities which are highly affected by the technological restriction in *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 only barely affected by the treatment constitute the control observations, classified as *Near*-light and defined by: $\kappa \leq \mu_\kappa - \sigma_\kappa$. All other municipalities are either of an intermediate κ and classified as *Near*-normal or *Remote*-only which exhibit a share of $\kappa = 0$ by default. Both of these groups are excluded from the analysis regarding technology regulation because they cannot be conclusively sorted into treatment or control groups.[23] The classification of municipality types according to their *Near*-share

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

thresholds is summarized in Equation 2.3.[24]

$$\text{Municipality Type} = \begin{cases} \textit{Near}\text{-heavy} & \kappa_i \geq \mu_\kappa + \sigma_\kappa \\ \textit{Near}\text{-normal} & \mu_\kappa - \sigma_\kappa < \kappa_i < \mu_\kappa + \sigma_\kappa \\ \textit{Near}\text{-light} & 0 < \kappa_i \leq \mu_\kappa - \sigma_\kappa \\ \textit{Remote}\text{-only} & \kappa_i = 0 \end{cases} \tag{2.3}$$

Table 2.5 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. This, together with a different age structure, indicates that treatment and control group observations cannot be considered equivalent ex-ante. Since those differing attributes might have influenced MDF placement in the past (see Section 2.3.2), selection into treatment might be non-random in this regard, necessitating a matching procedure.

Table 2.5: 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 (abs.)
Near-heavy	660	0.67	0.51	2.21	26.46	1256	1.13
Near-light	499	0.07	1.96	2.42	67.94	4024	1.47
Near-normal	3369	0.26	1.69	2.97	55	3652	1.59
Remote-only	6206	0	0.14	1.12	15.13	430	0

Notes: Comparison of key municipal characteristics by municipality type. For the thresholds defining the respective types, see Equation 2.3.

The procedure of choice is propensity score matching with the propensity being a municipality's probability of possessing a dense allocation of MDFs and thus a substantial *Near*-area. 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 federal state fixed effects to capture structural differences in MDF placements resulting from the German separation and post-war federalism in West Germany.[25] The Logit model used for the estimation of propensity scores is defined in Equation 2.4.[26]

$$Prob(\text{Near} = 1|LXY) = f\ (L'\alpha, \delta_1 Dens, \delta_2 Area, \delta_3 Houses, \zeta_1 Population) \tag{2.4}$$

[24] 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%) the data is insufficiently precise and thus yields ambiguous results. These observations are dropped prior to analysis.

[25] The actual data on municipality characteristics for this period is, unfortunately, not comprehensive, excluding the former GDR entirely and suffering from incomplete data-keeping for West German municipalities. Hence, the reliance on present-day data.

[26] For a more detailed look into the quality and choice of this specification, see Table 2.20 of the Appendix.

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 2.6 in comparison with Table 2.5. Specifically, matching with replacement reduces variation between the groups by 65% to 75%.[27]

Table 2.6: 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 (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 2.4, 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 drawing 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 municipality types, implying a common population with respect to actual and predicted deployment decisions.[28]

Since pre-period data for technology-specific network coverages is not available, we cannot test for the fulfillment of the parallel trends assumption directly. However, treatment and control observations are similar to the dropped out but comparable *Near*-normal municipalities with respect to the likelihood of FttP deployment and structural characteristics. Based on this and the conducted propensity score matching, we are confident that the matched sample most likely follows the same trend.

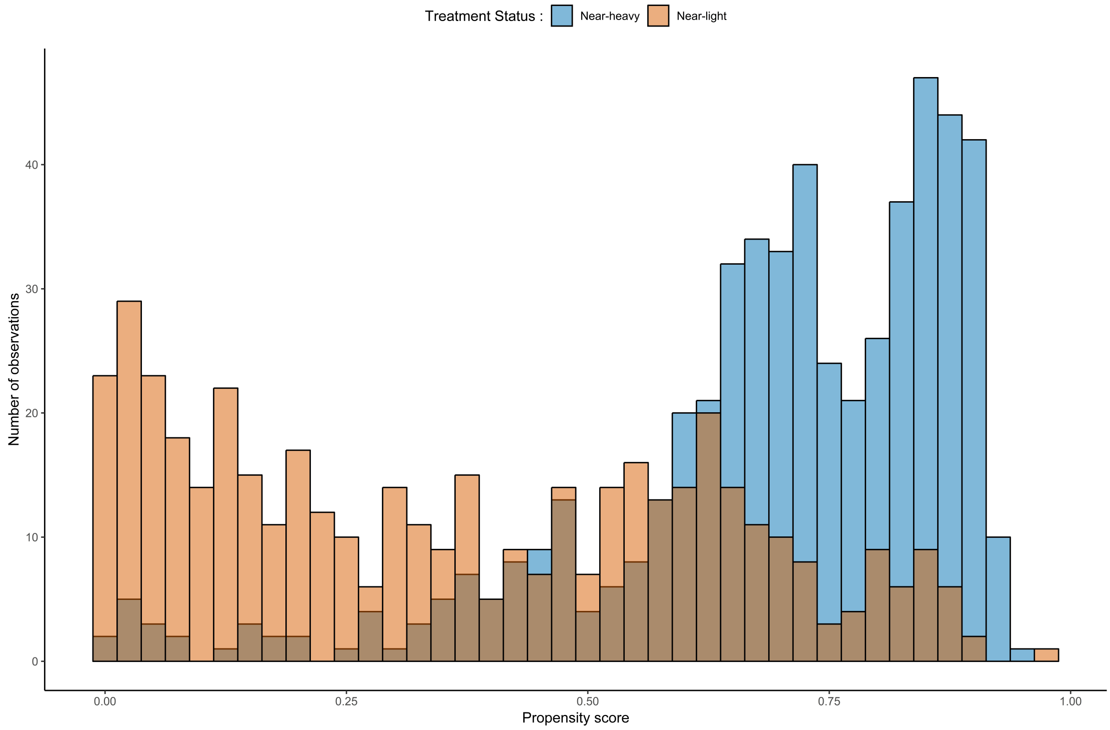
In terms of common support, the two groups have sufficient overlap for a qualified comparison (see Figure 2.4). Discrepancies do exist in the areas of higher propensity scores, pointing to limitations of the matching. But this deviance in the tails seems acceptable given the higher number of treatment 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 and not against selection into treatment, since MDF location and broadband expansion are decisions taken almost a century apart. Using the matched set, the average treatment effects are calculated as sample means and compared between treatment and control groups. We also apply an OLS estimation for robustness.

Subsidies The impact of subsidies as a driver of FttP expansion is assessed using the comprehensive program and recordings of the federal state of Bavaria. Extensive and

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

[28] Figure 2.5 in the Appendix displays this as a collection of scatter plots for the federal states.

Figure 2.4: Area of Common Support



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

intensive margin models are estimated equivalently to Equation 2.1 and Equation 2.2, without the federal state fixed effects. Thus, the subsidies become a singular addition to an otherwise unchanged set of characteristics, permitting comparison across models and subsets.

2.6 Results

2.6.1 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 - if sometimes miniscule - FttP expansion during the observation period (Δ *FttP* > 0). Out of 311 municipalities which were already accessed with FttP, 303 received further investments into the technology between 2013 and 2017 (see Table 2.7), 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, the general trends remain even when observing median values, which suggest a structural distinction between early accessed municipalities and all others.[29]

Table 2.7: Municipal characteristics by pre-existing FttP coverage

FttP.13> 0, ΔFttP > 0	Count	FttP.13	ΔFttP	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 accessed 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 accessed municipality on subsequent FttP expansion taking place stresses this risk.[30] Existing coverage in 2013 implies an expansion probability of near 100% in linear, Logit and Probit models (see Table 2.8). 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* $= 0$).

Extensive Margin FttP investment decisions at the extensive margin appear to be driven by elements from three of the four categories defined: Technology, market size and accessibility. Subsidies are insignificant on the federal level. Table 2.9 shows the estimations for the corresponding Logit and OLS regressions. The following analysis focuses on the OLS results.[31]

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 per 10 percentage points higher coverage.[32] Likewise, expansion of *Remote*-area Vectoring in the observation period raises the FttP investment probability by 0.5 percentage points per a 10 percentage point coverage increase. For *Remote*-only

[29]Median municipality characteristics relating to FttP coverage in 2013 are displayed in Table 2.14 of the Appendix.

[30]Being an early accessed municipality is captured by the dummy *F2013* which takes the value 1 if *FttP.13*> 0 and a value of 0 otherwise.

[31]Robust and federal state (*Länder*)-clustered standard errors have been calculated for these regressions and shown no changes in significance levels. In addition, the Appendix Table 2.16 summarizes the marginal effects derived from the results of the OLS regressions. In Table 2.17, 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 exceedingly rare, alleviating the potential shortcoming of OLS.

[32]The significant and positive effect of base Vectoring coverage in *Near*-areas does not invalidate the identification. Recall from Section 2.3.2 that Vectoring may be feasible in the outskirts of a given *Near*-area. Usually, these areas are located near 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.

Table 2.8: 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. 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.

municipalities, results are broadly similar: A higher base coverage of Vectoring raises investment probabilities by 1.5 percentage points per a 10 percentage point higher coverage. Vectoring expansion exerts a positive influence of 0.3 percentage points (per a 10 percentage points change). In relation to the average predicted investment probabilities of around 10% for *Near* & *Remote* municipalities and 8% for *Remote*-only ones, these effects are substantial.[33]

In contrast to Vectoring, the impact of HFC seems more ambiguous for FttP deployment. While the HFC base coverage in *Near*-areas positively impacts investment probability by 0.7 percentage points per 10 percentage points higher HFC coverage, its impact becomes negative in *Remote*-areas and insignificant for *Remote*-only municipalities. Additionally, the expansion of HFC networks is very rare, but nonetheless impacts FttP expansion positively in *Remote*-only municipalities by a 3 percentage point increase in probability if it occurs.[34]

Thus, the effect of alternative infrastructure technologies on the likelihood of FttP deployment appears to vary with the alternative. While the qualitatively inferior Vectoring exerts a positive influence both in form of coverage level and coverage increase, HFC's effect depends on whether it occurs in *Near*- or *Remote*-areas. Especially the

[33]The averages of the predicted investment probabilities are almost identical between linear and Logit models, which aligns well with the 10 and 9 percent of municipality types receiving deployment over the observation period.

[34]Note that *HFC.Exp.r* is a dummy variable, capturing solely the event of expansion, not the extent. For robustness, $\Delta HFC.r/n$ have been used but found to be non-relevant.

Table 2.9: 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)	4.32**	0.71***	0.60***	2.77·
	(1.59)	(0.13)	(0.09)	(1.46)
Vectoring.13.r	1.00	0.07	0.15***	2.18***
	(0.68)	(0.07)	(0.03)	(0.36)
Vectoring.13.n	1.80***	0.29***		
	(0.55)	(0.06)		
Δ Vectoring.r	0.61*	0.05*	0.03*	0.45*
	(0.26)	(0.02)	(0.01)	(0.21)
Δ Vectoring.n	0.25	0.01		
	(0.30)	(0.03)		
HFC.13.r	−0.85*	−0.07*	−0.03	−0.46
	(0.41)	(0.03)	(0.02)	(0.31)
HFC.13.n	0.84**	0.07**		
	(0.31)	(0.03)		
HFC.Exp.r			0.03*	0.44*
			(0.01)	(0.17)
nearby10k	0.45**	0.05***	0.09***	0.85***
	(0.15)	(0.01)	(0.01)	(0.16)
Age	−0.12***	−0.01***	−0.00·	−0.07*
	(0.04)	(0.00)	(0.00)	(0.03)
Density	0.01	0.00	−0.00	−0.01
	(0.02)	(0.00)	(0.00)	(0.05)
Area	0.01***	0.00***	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Ruggedness	−0.39**	−0.02·	0.01·	0.22·
	(0.14)	(0.01)	(0.01)	(0.13)
Min_MZ	−0.25**	−0.02***	−0.04***	−0.45***
	(0.08)	(0.01)	(0.01)	(0.11)
New Construction	4.77	0.45	0.78***	9.52**
	(3.56)	(0.33)	(0.23)	(3.10)
Länder FE	YES	YES	YES	YES
Log Likelihood	-1145.68			-876.53
Deviance	2291.37			1753.05
Num. obs.	4010	4010	3804	3804
R^2		0.10	0.20	
Adj. R^2		0.10	0.20	

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

Notes: Determinants are shown for *Near* & *Remote* municipalities 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.

result on Vectoring stands in contrast to Calzada *et al.* (2018) who find a negative influence of the number of Bitstream connections, a Vectoring equivalent, from the Spanish incumbent Telefonica on its own FttH deployment.[35] Based on these findings, extensive Vectoring structures may signal attractive deployment areas to competitors and can be seen as a complementary bridge technology for the extensive margin of FttP deployment.

The set of relevant technology variables is concluded by the dummy variable *nearby10k* which denotes whether a given municipality is adjacent to one with positive FttP coverage in 2013.[36] It captures a possible spillover of early FttP deployments into neighboring municipalities. This effect is found to be highly relevant and significant. The deployment of FttP becomes 5 percentage points more likely for municipalities with MDF and 9 percentage points more likely for those without if an early accessed municipality is in the proximity. A similar positive correlation with existing infrastructure has also been observed by Bourreau *et al.* (2018) with regards to legacy DSL connections. The radiating effect can be likened to an "expansion hub" in that an existing local network provider branches out into adjacent areas following a successful early deployment project.

Of the market size characteristics, only age is significant and relevant. Given their lack of impact or significance, other variables of the category are not included in the main extensive margin specification.[37] An additional year of average age within a municipality population reduces the expansion probability by one percentage point. Given a lesser interest of older people in digital services such as streaming or video gaming, this result is both intuitive and in line with prior literature.[38]

[35]As mentioned in Section 2.2, the fact that only FttH of the incumbent is being analyzed by Calzada *et al.* (2018) implies a negative bias of their estimates on infrastructure competition. Since the legacy infrastructure is also being operated and monetized by the incumbent, deployment incentives for FttH are automatically reduced in areas where sales from Bitstream unbundling, the Vectoring based wholesale product, are substantial (or, to put it differently, Vectoring coverage is high).

[36]Using the geographical centroid of a given municipality, the dummy *nearby10k* takes the value 1 if 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 first two moments of the area size distribution in the set. For robustness, thresholds of 5 and 25 kilometers were also considered. In an additional robustness check against an overlap with area size or agglomeration effects, variables for proximity to a city of at least 100,000 and 500,000 inhabitants were computed in the same manner. Their inclusion did not alter results.

[37]A broader analysis including all covariates is summarized in Table 2.15 of the Appendix. Were population included in the main specification, it would also positively impact the deployment likelihood and be significant. However, its correlation with area and population density might cause multicollinearity defects. Area size and population density, on the other hand, are sufficiently uncorrelated on account of the definition of municipality borders. These were driven by the goal of homogenizing population counts during the West-German municipality territory reform in 1967.

Moreover, population is an imprecise measure as it captures not solely the size effect of the customer count, but also a potential stochastic effect: If all households were equally likely to receive FttP, municipalities with larger populations would enjoy a greater deployment likelihood just by increased chance. Inclusion of the variable also does not significantly improve the quality of the extensive margin estimations, while its exclusion does not bias or change results (see Table 2.15). For these reasons, population is excluded from the main specifications.

[38]Literature examples for the effect of age on infrastructure deployment are numerous, but for a specific fiber context see Calzada *et al.* (2018). The observed effect of age is robust to using the share of people older than 60 years, adding a squared age variable or using the mean difference of

Accessibility measures appear more relevant in comparison. Only density, typically considered a key factor, is not significant for either municipality type. This divergence from literature may partially result from its influence on legacy infrastructure. Population density also shaped the deployment of cable- and copper-networks which in turn determine, through HFC and Vectoring, the profitability of FttP and the intensity of technology competition today. Hence, these competing technologies are more relevant for FttP deployment than is the density itself. Moreover, the typically observed economies of density are most prevalent in urban agglomerations, of which the largest and most dense are excluded from this analysis due to positive FttP coverage in 2013.

A municipality's area impacts deployment probability positively for *Near* & *Remote* municipalities. This effect becomes insignificant and negative for *Remote*-only observations, reflecting the dual nature of area: If populated, it increases investment opportunities, but an underpopulated rural area signals higher deployment costs.[39] Structural seclusion, measured as Min_MZ, the driving distance to the nearest medium-sized town, reduces deployment probability by 2 percentage points for 10 additional minutes for municipalities with MDF. This effect doubles for *Remote*-only municipalities, which is one of the most pronounced effects in the analysis and implies a more severe effect for smaller municipalities. Briglauer *et al.* (2019) also used this variable in their analysis and found it to be insignificant for their set of Bavarian municipalities, as do we in the Bavarian subset. This is likely a result of Bavaria's more rural and homogeneous spatial structure.

Similarly, the ruggedness of terrain, a proxy for construction costs of the required ductwork, adversely impacts the likelihood of deployment for municipalities with MDFs by 2 percentage points per 100 meters of average elevation heterogeneity. Interestingly, this negative influence disappears for *Remote*-only municipalities. The quota of newly constructed residential buildings exerts a positive effect on deployment probability in *Remote*-only municipalities. An additional percentage point in this share corresponds to a higher probability of FttP deployment by 0.78 percentage points. This *Remote*-only exclusive effect may indicate the higher dependence of those municipalities on new residential housing, which require new wiring, to trigger FttP deployment.[40]

Intensive Margin Once a municipality is chosen for FttP expansion, an operator needs to decide on the deployment extent. That extent likewise depends on factors subsumed under the categories technology, market size and accessibility. Table 2.10 displays the estimated OLS regression results for FttP expansion at the intensive mar-

a population's average age. Lastly, higher population ages could correlate with rural or structurally weak areas, but the age effect is robust to the inclusion of proxy variables for this such as income per capita and industrial area.

[39] More general spatial and political features are captured by the federal state (*Länder*) fixed effects (NUTS 1), which are highly relevant. For robustness, the following alternative fixed effects have been used: *Regierungsbezirke*, *Kreise* and *Reisegebiete*. The first two are less aggregated administrative units (NUTS 2 and 3), whereas the last captures tourist areas and, therein, similarities in geography and structure. Their aggregation level lies between the other two fixed effect alternatives. Overall results remain qualitatively unchanged.

[40] Note that we cannot distinguish from the data whether the expansion occurs solely to connect the new properties or acts as an initial trigger for wider deployment.

gin for municipalities which received FttP expansion.[41]

Table 2.10: Determinants of FttP expansion at the intensive margin

Endogeneous Variable:	Δ FttP	
Municipality	Near & Remote	Remote-only
	(1)	(2)
(Intercept)	1.41***	1.78***
	(0.37)	(0.38)
Δ Vectoring.r	−0.14**	−0.24***
	(0.04)	(0.04)
Age	−0.01·	−0.02**
	(0.01)	(0.01)
Income p. capita	−0.00·	0.00
	(0.00)	(0.00)
Density	−0.01*	−0.02
	(0.00)	(0.01)
New Construction	−1.50·	−0.24
	(0.77)	(0.70)
Area	−0.001***	−0.005**
	(0.00)	(0.00)
Ruggedness	−0.10*	0.06
	(0.04)	(0.05)
Länder FE	YES	YES
R^2	0.35	0.54
Adj. R^2	0.32	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: ΔFttP > 0. The endogenous variable 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. The change in Vectoring coverage negatively impacts FttP deployment intensity by 1.4 percentage points per a 10 percentage point increase in coverage for municipalities with MDFs. For *Remote*-only ones, this effect increases to 2.4 percentage points. Both results imply a substitutive rather than complementary effect of Vectoring for FttP expansion, which would support the European Commission's view. Hence, a simultaneous roll-out of Vectoring appears to partially foreclose - in a loose application of the term - the respective area to FttP deployment. At 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

[41] For these estimates, robust and federal state (*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 categories and their effects on the intensive margin, see Table 2.18 in the Appendix.

relationship. The level of early Vectoring coverage signals an attractive market, but competition in the form of increasing Vectoring coverage curtails the areas in which FttP could be expanded profitably. Thus, the effect of Vectoring is ambiguous: It may cause FttP investment in municipalities that would not have been sufficiently attractive otherwise, but simultaneously limits the intensity of deployment.

Of the market size characteristics, the average age and available income per capita 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 and only for municipalities with MDF but its coefficient has a negative sign, which is implausible, stands in contrast to prior literature findings and remains puzzling to the authors.[42]

The relevant accessibility characteristics all impede deployment intensity. In contrast to the extensive margin results, population density is significant for municipalities with MDFs, its coefficient implying a 1 percentage point reduction for an additional 100 inhabitants per square kilometer. Density can thus be thought of as a cost driver: Densely populated areas imply a higher degree of urbanization and households requiring connection, complicating construction procedures. While the number of FttP connections increases with density, the share of households connected decreases; hence the lack of significance for *Remote*-only municipalities, which are more sparsely populated in general.[43]

A municipality's area exhibits a negative effect on the intensive margin ranging from 0.1 percentage points less coverage expansion per 10 km^2 for municipalities with *Near*-areas to 0.5 percentage points less expansion for those without. As a greater area implies longer cable lengths to connect the households in question, construction likewise becomes more expensive.[44] Terrain ruggedness decreases deployment intensity by 10 percentage points per additional 100 meters of elevation heterogeneity for municipalities with MDFs, while the variable is non-significant for *Remote*-only municipalities.[45] This reflects both the postulated cost increase of more rugged terrain and divergent cost calculations for *Remote*-only municipalities.

New residential housing also has a negative impact on the intensity of FttP expansion for *Near* & *Remote* municipalities. This mirrors the positive effect for *Remote*-only municipalities observed at the extensive margin in that it induces FttP expansion where

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

[43]The estimated negative effect of population density on FttP deployment stands in contrast to findings of Calzada *et al.* (2018) and Bourreau *et al.* (2018) which suggest the interpretation of density as a positive market size increasing measure. However, our distinction between *Remote*-only and *Near* & *Remote* municipalities probably captures this market size effect in the higher deployment probabilities for the latter type, revealing the cost driving effect of population density. Also, the exclusion of early FttP-accessed municipalities, which are on average also more densely populated, further limits the observability of this positive effect.

[44]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.

[45]Note that the mean of elevation heterogeneity for municipalities with MDFs is at 0.67 and at 0.4 for municipalities without MDFs.

it would not have occurred otherwise. Here, it corresponds to a limitation of the deployment intensity and does not seem to trigger additional FttP connections beyond the initial property.

Lastly, as stated in Section 2.5.1, 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.[46] In consequence, the first two main results regarding FttP expansion are summarized below.

Result 1: Demographic, structural and topographic characteristics are relevant indicators for FttP deployment on the municipal level. Of these, the population's average age, the ruggedness of terrain, its seclusion and the share of new residential buildings are 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.

2.6.2 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 2.3.2), the interactions between these two technologies can be defined more clearly. The matching procedure presented in Section 2.5.2 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.[47] If the matching is conducted without replacement, 451 treatment and control units each remain in the dataset. For both sets, descriptive statistics and mean values for the Vectoring expansion are provided in Table 2.11. Notably, the predicted probabilities for expansion are similar for treated and non-treated municipalities.[48]

The treatment has a significant impact only in the subset generated by matching without replacement (see Table 2.12 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 as the subset suffers from a deterioration in

[46]The regression results are displayed in Table 2.19 in the Appendix. Notably, income per capita loses significance when accounting for a potential selection. However, federal state (*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.

[47]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 2.21 in the Appendix).

[48]The predicted deployment probabilities stem from the main extensive margin specification in Section 2.6.1 and are displayed in column 5 of Table 2.11.

Table 2.11: Mean characteristics for matched municipalities

Municipality Type	FttP.Exp= 1	Count	Δ FttP	P(FttP.Exp= 1)	Δ Vectoring.r
Municipality statistics, matching with replacement:					
Near-heavy	No	488	0	0.08	0.19
Near-heavy	Yes	51	0.37	0.2	0.23
Near-light	No	156	0	0.09	0.25
Near-light	Yes	17	0.31	0.19	0.29
Municipality statistics, matching without replacement					
Near-heavy	No	412	0	0.08	0.19
Near-heavy	Yes	39	0.38	0.18	0.25
Near-light	No	406	0	0.11	0.3
Near-light	Yes	45	0.2	0.2	0.33

Notes: Descriptive statistics for the matched treatment (*Near*-heavy) and control (*Near*-light) subset based on propensity scores. Sample means for the technology variable of interest are provided for both matching with and without replacement.

matching quality. Structural characteristics and predicted extensive margin probabilities differ more substantially when matched without replacement, yielding a control group of, on average, larger and more populous municipalities. 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. All of this limits the validity of the results for matching without replacement.

Table 2.12: Average treatment effects

		Matching			
		With Replacement		Without Replacement	
		Treat	Control	Treat	Control
	Count:	539	173	451	451
Ext. Margin	FttP.Exp= 1:	0.095	0.098	0.086	0.100
	$Pr(>\|t\|)$	0.888		0.4923	
	Count:	51	17	39	45
Int. Margin	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.

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 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 analysis of the technology-restrictive regulation provides only weak support for the previously observed result at the intensive margin of FttP deployment, though. Vectoring expansion can be detrimental to fiber deployment intensity. It seems reasonable to assume that Vectoring exhibits competitive pressure on FttP operators, thus limiting the intensity of their deployments. A policy specifically alleviating this pressure could only be reasonably effective - if at all - at the intensive margin.

Subsidies Repeating the analyses of Section 2.6.1 for the federal state of Bavaria permits the inclusion of its comprehensive subsidy program on the municipality level. Table 2.13 displays the estimated OLS 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 FttP expansion projects in a given municipality increases the probability of FttP investment by 3 percentage points.[49] For *Remote*-only municipalities, the effect increases to 4 percentage points. Note that only five percent of Bavaria's *Remote*-only municipalities and eight percent of its *Near* & *Remote* municipalities see any FttP expansion. Consequently, a subsidy of 100,000 Euro increases the expansion probability of a typical Bavarian municipality by 12.5 to 40 percent. This result supplements the finding of Briglauer *et al.* (2019) who prove the general effectiveness of the Bavarian subsidy program with respect to the occurrence of broadband deployment.

However, this result 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 measures are not as relevant due to this homogeneity in localities and the exclusion of large cities on account of FttP existing 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 in 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.[50] These findings are reflective of the lower levels of broadband expansion and coverage in Bavaria compared to the whole of Germany during the observation period.

Subsidies also have no significant effect on FttP deployment at the intensive mar-

[49] Bavaria also subsidized FttX deployment projects which would have included Vectoring solutions. A regression of such, non-FttP subsidies on FttP 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.

[50] See Footnote 32 for the explanation on such expansion.

Table 2.13: 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)	-6.20	-0.25	-0.48^{*}	-12.19^{**}
	(4.25)	(0.26)	(0.23)	(4.64)
Vectoring.13.r	1.99	$0.18^{\cdot}$	0.24^{***}	3.33^{***}
	(1.35)	(0.10)	(0.05)	(0.76)
Vectoring.13.n	1.67	$0.23^{\cdot}$		
	(1.38)	(0.12)		
Δ Vectoring.r	-0.12	-0.01	0.06^{*}	1.18^{*}
	(0.64)	(0.05)	(0.03)	(0.57)
Δ Vectoring.n	1.65^{*}	0.15^{**}		
	(0.74)	(0.06)		
HFC.13.r	-0.96	-0.07	0.03	0.66
	(1.05)	(0.08)	(0.04)	(0.73)
HFC.13.n	1.13	0.08		
	(0.73)	(0.05)		
HFC.Exp.r			-0.01	-0.22
			(0.02)	(0.46)
nearby10k	0.87^{**}	0.08^{**}	0.07^{***}	1.17^{***}
	(0.31)	(0.02)	(0.02)	(0.34)
Age	0.07	0.01	0.01^{*}	$0.18^{\cdot}$
	(0.09)	(0.01)	(0.01)	(0.11)
Density	-0.03	-0.00	-0.00	-0.09
	(0.05)	(0.00)	(0.01)	(0.15)
Area	0.01^{**}	0.00^{**}	0.00^{*}	0.02^{*}
	(0.00)	(0.00)	(0.00)	(0.01)
Ruggedness	-0.51^{*}	-0.02^{*}	-0.01	-0.22
	(0.23)	(0.01)	(0.01)	(0.25)
Min_MZ	-0.30	-0.02	0.00	0.15
	(0.26)	(0.02)	(0.02)	(0.37)
New Construction	-16.50	-0.84	-0.05	-2.40
	(11.87)	(0.63)	(0.48)	(11.57)
Funding until 2015	0.26^{***}	0.03^{***}	0.04^{***}	0.37^{***}
	(0.06)	(0.01)	(0.01)	(0.08)
Log Likelihood	-221.26			-168.77
Deviance	442.53			337.54
Num. obs.	942	942	905	905
R^2		0.10	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 2.9. The probability of expansion in a given municipality is estimated using Logit - (1) and (4) - and OLS - (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.

gin.[51] Their coefficient is, however, negative, which would seem logical as municipalities accessed only on account of subsidies would likely be less attractive to expand further than those expanded without receiving 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 being accessed with FttP for a given municipality. Deployment intensity is not adversely affected by such a regulation.

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

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

On the micro-level, structural and topographic conditions are found to be decisive supply-side factors in explaining the locations chosen for FttP deployment and the intensity of that expansion. A population's age, the ruggedness of terrain, the seclusion of a municipality and the share of newly built residential housing are strongly associated with the probability for FttP deployment. Additionally, early fiber-accessed municipalities emit a kind of spillover effect on their neighbors and raise 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 of Vectoring is associated with a more likely FttP deployment, an increase in coverage reduces the intensity of FttP expansion.

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 significantly to the deployment restrictions. The removal of Vectoring as a competing infrastructure shows no reliable effect. However, state intervention in the form of subsidies is effective. An additional funding of 100,000€ increases the FttP deployment probability of a municipality by 3 to 4 percentage points, corresponding to a 12.5% to 40% change given the average deployment probability. However, this only applies to funding for FttP-specific projects.

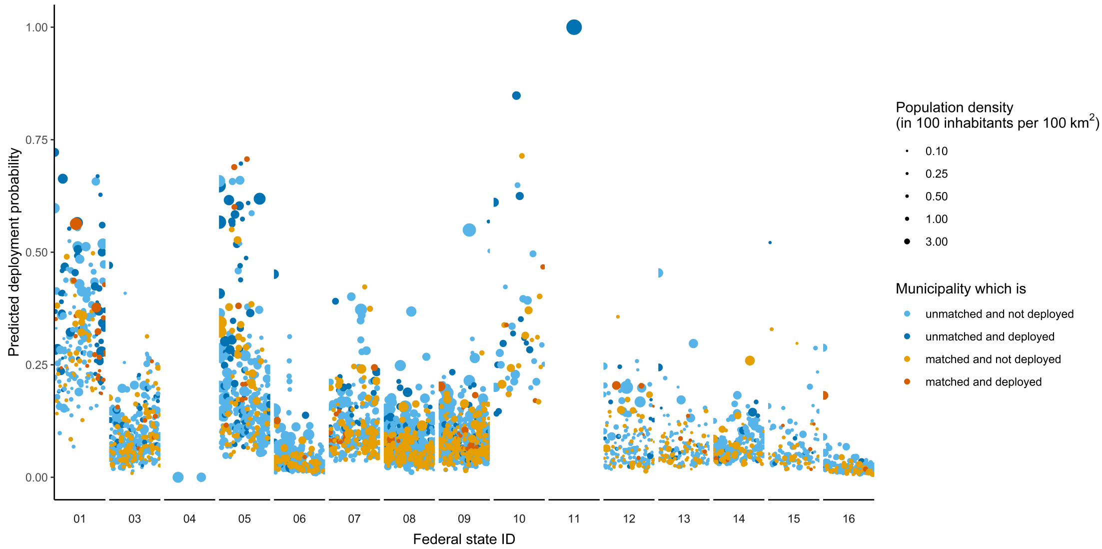
Therefore, the main challenge for policymakers in shaping the infrastructure upgrading process is to offset the structural conditions that determine the FttP roll-out

[51] Table 2.22 displays the corresponding regression results and compares them to the results for all of Germany. *Remote*-only municipalities are not considered because too few of those with FttP deployment received subsidies in Bavaria for an OLS regression to provide consistent results.

at the local level. 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 "expansion hubs" might decrease costs of FttP deployment for neighboring municipalities, reinforcing the positive deployment effect.

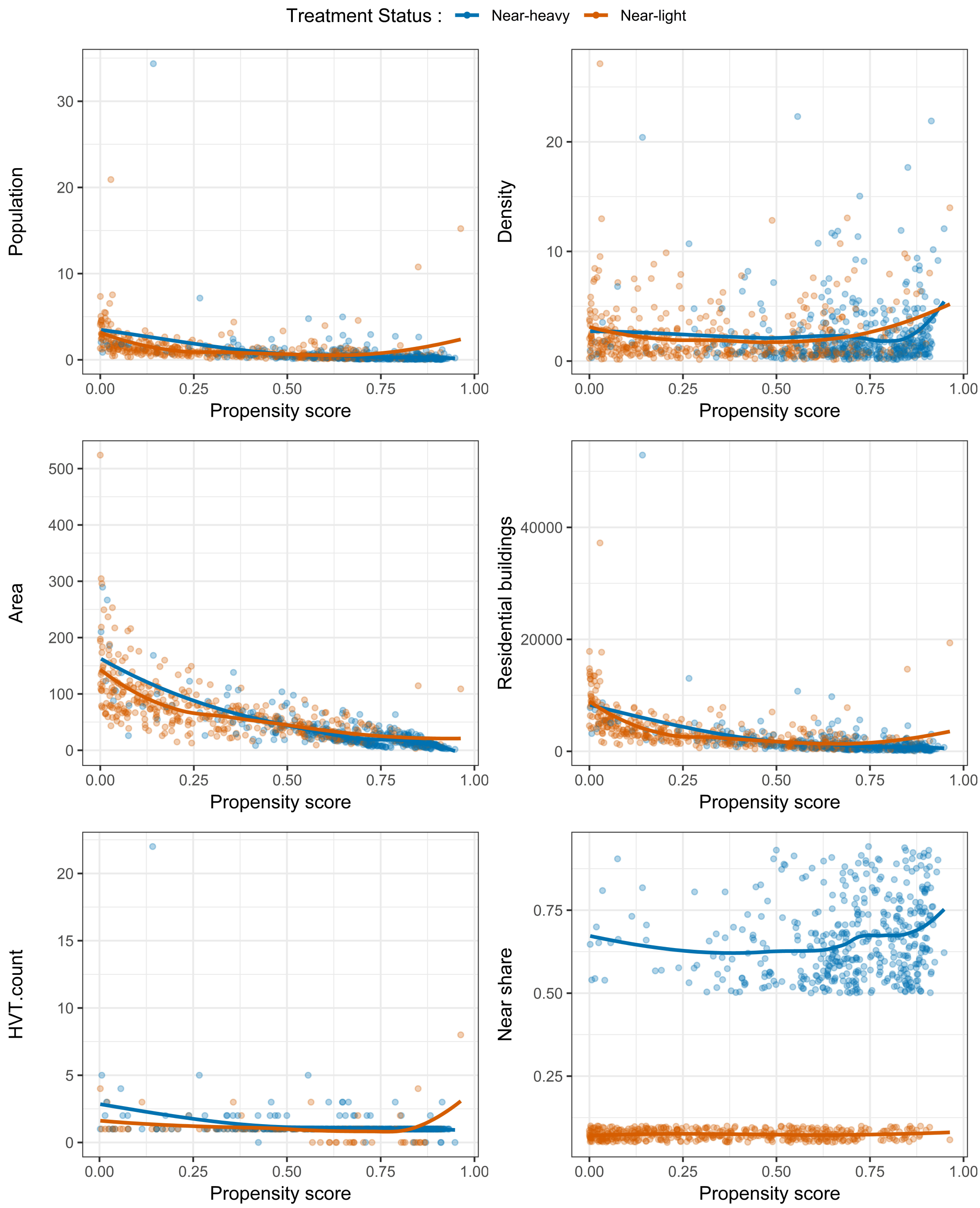
Appendix A

Figure 2.5: Balance of matched municipalities by federal state



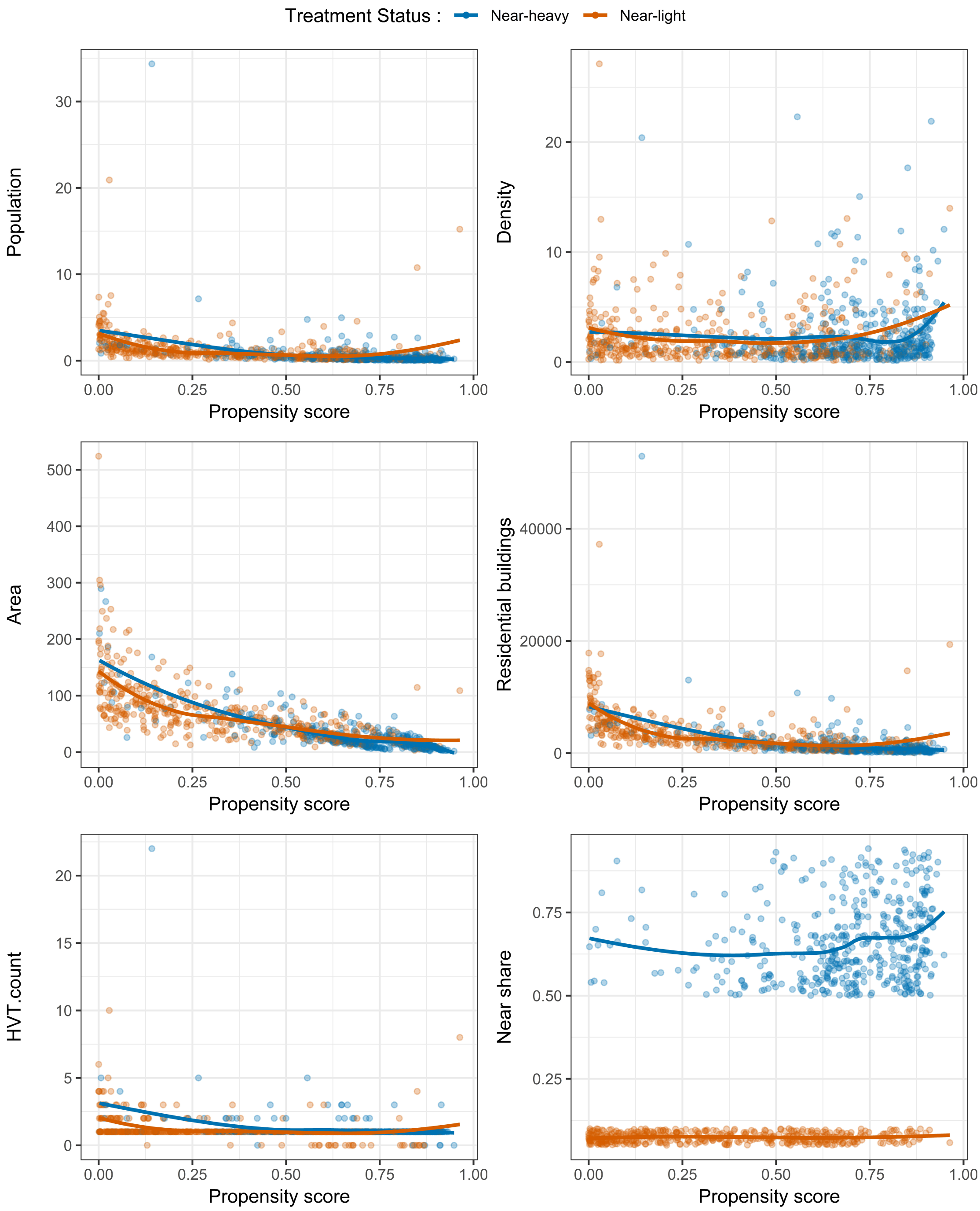
Notes: Municipalities are displayed with respect to their predicted FttP deployment probabilities. Colours refer to their status as either treatment or control group and to their actual deployment status. The scatter plots are sorted by federal state. The IDs correspond to these states in the following 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 2.6: 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 2.7: 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 2.14: 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 (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 (Δ FttP >0) and did not receive expansion (Δ FttP $=0$) during the observational period.

Table 2.15: 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^{**}	0.89^{***}	0.33^{***}	0.32^{***}	0.72^{***}	0.71^{***}
	(0.06)	(0.13)	(0.06)	(0.02)	(0.14)	(0.13)
Vectoring.13.r	0.10				0.06	0.07
	(0.07)				(0.07)	(0.07)
Vectoring.13.n	0.28^{***}				0.28^{***}	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^{**}				0.05^{*}	0.05^{*}
	(0.02)				(0.02)	(0.02)
Δ Vectoring.n	0.02				0.01	0.01
	(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	$0.04^{\cdot}$					
	(0.02)					
HFC.Exp.n	-0.02					
	(0.02)					
HVT.count	0.01^{***}		0.00		-0.01	
	(0.00)		(0.00)		(0.01)	
Houses		0.00^{***}			0.00	
		(0.00)			(0.00)	
Population		-0.02^{**}			0.00	
		(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			0.00		-0.00	0.00
			(0.00)		(0.00)	(0.00)
Single-Family Houses			-0.01			
			(0.07)			
New Construction			0.84^{*}		0.45	0.45
			(0.33)		(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)	
Ruggedness			-0.02^{*}		-0.01	$-0.02^{\cdot}$
			(0.01)		(0.01)	(0.01)
Min_MZ			-0.03^{***}		-0.02^{**}	-0.02^{***}
			(0.01)		(0.01)	(0.01)
Min_A			0.00		0.00	
			(0.00)		(0.00)	
nearby10k			0.06^{***}		0.05^{***}	0.05^{***}
			(0.01)		(0.01)	(0.01)
Subsidies				0.00^{*}	0.00	
				(0.00)	(0.00)	
Länder FE	YES	YES	YES	YES	YES	YES
R^2	0.09	0.08	0.08	0.06	0.10	0.10
Adj. R^2	0.08	0.07	0.08	0.05	0.10	0.10
Num. obs.	4010	4010	4010	4010	4010	4010

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

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 2.16: Coefficient interpretation for the main extensive margin OLS specification

Variable	Δ	*Near* & *Remote*	*Remote*-only
Vectoring.13.r	10 pp	-	1.5 pp
Vectoring.13.n	10 pp	2.9 pp	
Δ Vectoring.r	10 pp	0.5 pp	0.3 pp
Δ Vectoring.n	10 pp	-	
HFC.13.r	10 pp	-0.7 pp	-
HFC.13.n	10 pp	0.7 pp	-
Age	1 year	-1 pp	-0.4 pp
Density	$\frac{100 \text{ Inhabitants}}{km^2}$	-	-
Area	10 km^2	0.6 pp	-
nearby10k	0/1	5 pp	9 pp
Ruggedness	100m	2 pp	1 pp
Min_MZ	10 min.	2 pp	4 pp
New Construction	1 pp	-	0.8 pp
HFC.Exp.r	10 pp	-	0.3 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 2.9). 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% for *Near* & *Remote* municipalities and 9% for *Remote*-only. The respective median values are at 8 and 5.

Table 2.17: Average marginal effects for the main extensive margin Logit specification

Endogeneous Variable:	FttP.Exp [0,1]	
	Near & Remote	Remote-only
	(1)	(2)
(Intercept)	0.35*	0.18·
	(0.14)	(0.10)
Vectoring.13.r	0.08	0.14***
	(0.06)	(0.02)
Vectoring.13.n	0.15**	
	(0.05)	
Δ Vectoring.r	0.05*	0.03*
	(0.02)	(0.01)
Δ Vectoring.n	0.02	
	(0.02)	
HFC.13.r	−0.07·	−0.03
	(0.04)	(0.02)
HFC.13.n	0.07*	
	(0.03)	
Age	−0.01**	−0.00*
	(0.00)	(0.00)
Density	0.00	−0.00
	(0.00)	(0.00)
Area	0.00***	0.00
	(0.00)	(0.00)
nearby10k	0.04*	0.06***
	(0.02)	(0.01)
Ruggedness	−0.03*	0.01
	(0.01)	(0.01)
Min_MZ	−0.02**	−0.03***
	(0.01)	(0.01)
New Construction	0.39	0.61**
	(0.30)	(0.21)
HFC.Exp.r		0.02*
		(0.01)
Länder FE	YES	YES
Log Likelihood	-1145.68	-876.53
Deviance	2291.37	1753.05
Num. obs.	4010	3804

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

Notes: The table displays average marginal effects for the Logit models used in the main results displayed in Table 2.9. The first column shows results for *Near* & *Remote* municipalities, whereas the second column shows results for *Remote*-only municipalities. Coefficients and significance levels 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 2.18: 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***	1.24***	0.47*	1.26**	1.41***	0.71***
	(0.04)	(0.36)	(0.18)	(0.44)	(0.37)	(0.13)
Vectoring.13.r	0.28*			0.27*		0.07
	(0.13)			(0.14)		(0.07)
Vectoring.13.n	−0.08			−0.09		0.29***
	(0.11)			(0.11)		(0.06)
Δ Vectoring.r	−0.04			−0.04	−0.14**	0.05*
	(0.06)			(0.06)	(0.04)	(0.02)
Δ Vectoring.n	−0.12·			−0.11		0.01
	(0.06)			(0.06)		(0.03)
HFC.13.r	−0.11			−0.08		−0.07*
	(0.09)			(0.10)		(0.03)
HFC.13.n	−0.03			−0.02		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)		
Age		−0.01·		−0.01	−0.01·	−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)
Single-Family Houses			0.10	−0.04		
			(0.22)	(0.23)		
New Construction			−1.41·	−1.62*	−1.50·	0.74
			(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	−0.02		
			(0.02)	(0.02)		
HVT.count			0.01	−0.04*		
			(0.01)	(0.02)		
Ruggedness			−0.13**	−0.11*	−0.10*	−0.02·
			(0.05)	(0.05)	(0.04)	(0.01)
nearby10k			−0.05	−0.04		0.05***
			(0.03)	(0.03)		(0.01)
Min_MZ						−0.02***
						(0.01)
Länder FE	YES	YES	YES	YES	YES	YES
R^2	0.34	0.31	0.33	0.39	0.35	0.10
Adj. R^2	0.30	0.28	0.29	0.33	0.32	0.10
Num. obs.	409	409	409	409	409	4010

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

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 2.19: Determinants of FttP expansion at the intensive margin - Heckman selection correction

Endogeneous Variable:	Δ FttP	
Municipality	N&R	R
(Intercept)	1.41^{***}	1.68^{***}
	(0.39)	(0.41)
Land.North	-0.09	0.07
	(0.06)	(0.09)
Land.South	-0.24^{***}	-0.39^{***}
	(0.06)	(0.08)
Land.West	-0.21^{***}	-0.32^{***}
	(0.06)	(0.09)
Δ Vectoring.r	-0.21^{***}	-0.25^{***}
	(0.04)	(0.04)
Age	-0.01	-0.02^{*}
	(0.01)	(0.01)
Income p. capita	$-0.00^{\cdot}$	0.00
	(0.00)	(0.00)
Density	-0.00	$-0.02^{\cdot}$
	(0.00)	(0.01)
New Construction	-1.98^{*}	-0.72
	(0.79)	(0.71)
Area	-0.00^{***}	-0.01^{***}
	(0.00)	(0.00)
Ruggedness	-0.10^{**}	0.05
	(0.04)	(0.05)
IMRI	-0.12^{**}	-0.05
	(0.04)	(0.05)
R^2	0.47	0.80
Adj. R^2	0.46	0.79
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 2.9 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 2.9 and Table 2.10, 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 2.20: 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**	0.71***
	(0.01)	(0.09)	(0.01)	(0.09)	(0.13)
Population	0.03***	0.03***		0.01	
	(0.00)	(0.00)		(0.00)	
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)	
Single-Family Houses		0.09*		0.06·	
		(0.04)		(0.04)	
New Construction		−0.00		−0.03	0.45
		(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***	
			(0.00)	(0.01)	
HVT.density.geo			1.53***	1.47***	
			(0.07)	(0.09)	
Vectoring.13.r					0.07
					(0.07)
Vectoring.13.n					0.29***
					(0.06)
Δ Vectoring.r					0.05**
					(0.02)
Δ Vectoring.n					0.01
					(0.03)
HFC.13.r					−0.07·
					(0.03)
HFC.13.n					0.07**
					(0.03)
nearby10k					0.05***
					(0.01)
Ruggedness					−0.02·
					(0.01)
Min_MZ					−0.02***
					(0.01)
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 2.21: 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)	1.35***	0.71***	0.20	1.41***
	(0.23)	(0.13)	(0.93)	(0.37)
Vectoring.13.r	−0.11	0.07		
	(0.12)	(0.07)		
Vectoring.13.n	0.37***	0.29***		
	(0.11)	(0.06)		
Δ Vectoring.r	0.01	0.05*	−0.37**	−0.14**
	(0.04)	(0.02)	(0.14)	(0.04)
Δ Vectoring.n	0.00	0.01		
	(0.05)	(0.03)		
HFC.13.r	−0.09	−0.07*		
	(0.06)	(0.03)		
HFC.13.n	0.11*	0.07**		
	(0.05)	(0.03)		
Age	−0.02***	−0.01***	0.02	−0.01·
	(0.01)	(0.00)	(0.02)	(0.01)
Density	−0.00	0.00	0.01	−0.01*
	(0.00)	(0.00)	(0.01)	(0.00)
Area	0.00	0.00***	−0.00·	−0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
nearby10k	0.05*	0.05***		
	(0.03)	(0.01)		
Ruggedness	0.01	−0.02·	−0.16	−0.10*
	(0.02)	(0.01)	(0.14)	(0.04)
Min_MZ	−0.01	−0.02***		
	(0.01)	(0.01)		
New Construction	0.16	0.45	1.98	−1.50·
	(0.57)	(0.33)	(2.48)	(0.77)
Income p. capita			−0.01·	−0.00·
			(0.01)	(0.00)
Länder FE	YES	YES	YES	YES
R^2	0.14	0.10	0.46	0.35
Adj. R^2	0.12	0.10	0.32	0.32
Num. obs.	991	4010	97	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 2.22: Determinants of FttP expansion at the intensive margin - Bavarian subset

Endogeneous Variable:	Δ FttP			
	Bavaria	Germany	Bavaria	Germany
	TYXS		TYXS.cons	
(Intercept)	1.50	1.26**	1.49·	1.41***
	(0.91)	(0.44)	(0.87)	(0.37)
Vectoring.13.r	0.92***	0.27*		
	(0.25)	(0.14)		
Vectoring.13.n	−0.60*	−0.09		
	(0.26)	(0.11)		
Δ Vectoring.r	−0.01	−0.04	−0.01	−0.14**
	(0.10)	(0.06)	(0.08)	(0.04)
Δ Vectoring.n	−0.03	−0.11		
	(0.11)	(0.06)		
HFC.13.r	−0.12	−0.08		
	(0.16)	(0.10)		
HFC.13.n	0.01	−0.02		
	(0.11)	(0.08)		
Houses	−0.00	0.00		
	(0.00)	(0.00)		
Population	0.27·	0.02·		
	(0.14)	(0.01)		
Age	−0.03	−0.01	−0.03	−0.01·
	(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	0.01	−0.01*
	(0.01)	(0.01)	(0.01)	(0.00)
Single-Family Houses	−0.37	−0.04		
	(0.37)	(0.23)		
New Construction	−1.63	−1.62*	−2.58	−1.50·
	(2.29)	(0.77)	(2.36)	(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	−0.10	−0.02		
	(0.10)	(0.02)		
HVT.count	−0.02	−0.04*		
	(0.06)	(0.02)		
nearby10k	−0.04	−0.04	−0.03	
	(0.05)	(0.03)	(0.05)	
Ruggedness	−0.01	−0.11*	−0.03	−0.10*
	(0.07)	(0.05)	(0.06)	(0.04)
Min_MZ	0.02		0.05	
	(0.04)		(0.04)	
Min_A	0.00		0.00	
	(0.00)		(0.00)	
Funding until 15	0.01		−0.00	
	(0.01)		(0.01)	
Länder FE	NO	YES	NO	YES
R^2	0.40	0.39	0.14	0.35
Adj. R^2	0.14	0.33	-0.01	0.32
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 2.10). 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 2.23: Summary statistics for technology (T) variables

Variable	Count	Mean	Median	St. Dev.	Min	Max
F2013	11,183	0.028	0	0.164	0	1
FttP.Exp	11,183	0.113	0	0.316	0	1
FTTP.13.r	11,183	0.009	0	0.085	0	1
Δ FttP.r	11,183	0.034	0	0.161	0	1
FTTP.13.n	4,972	0.008	0	0.069	0	1
Δ FttP.n	4,972	0.020	0	0.131	0	1
Vectoring.Exp.r	11,183	0.957	1	0.202	0	1
Vectoring.13.r	11,183	0.078	0.029	0.146	0	1
Δ Vectoring.r	11,183	0.241	0.071	0.318	0	1
Vectoring.Exp.n	4,972	0.935	1	0.247	0	1
Vectoring.13.n	4,972	0.063	0.034	0.114	0	1
Δ Vectoring.n	4,972	0.208	0.041	0.276	0	1
HFC.Exp.r	11,183	0.402	0	0.490	0	1
HFC.13.r	11,183	0.157	0	0.297	0	1
Δ HFC.r	11,183	0.031	0	0.137	0	1
HFC.Exp.n	4,972	0.511	1	0.500	0	1
HFC.13.n	4,972	0.304	0	0.415	0	1
Δ HFC.n	4,972	0.057	0	0.209	0	1
HVT.count	10,972	0.656	0	2.185	0	132
HVT.dens.geo	10,948	0.019	0	0.038	0	0.80
nearby10k	9,937	0.118	0	0.322	0	1

Notes: Summary statistics for all variables contained in the technology (T) category. The complete list of information on all used variables including their scale of measurement can be found in Table 2.24.

Table 2.24: Variable List

Variable	Description	contained in:	appears in Analysis Table:
Technology (T)			
FttP.13	FttP coverage in 2013 in Municipality	T	7, 14
F2013	Dummy, whether FttP coverage was positive (1) by the end of 2013	$T_{E,13}$	7
FttP.13.r	FttP coverage in 2013 in Remote area	T	
FttP.13.n	FttP coverage in 2013 in Near area	T	
FttP.Exp	Dummy, whether FttP coverage changed (1) from 2013-17	Dep.var	7 - 9, 11 - 13, 15
Δ FttP	Change in FttP coverage from 2013-17	Dep.var	10 - 12, 14, 17, 19
Vectoring.13.r	Vectoring coverage in 2013 in Remote area	T	9, 13, 15 - 17, 18, 20 - 22
Vectoring.13.n	Vectoring coverage in 2013 in Near area	T	9, 13, 15 - 17, 18, 20 - 22
Vectoring.Exp.r	Dummy, whether Vectoring coverage changed (1) from 2013-17 in Remote area	T_E	15
Vectoring.Exp.n	Dummy, whether Vectoring coverage changed (1) from 2013-17 in Near area	T_E	15
Δ Vectoring.r	Change in Vectoring coverage from 2013-17 in Remote area	T_E, T_I	9 - 11, 13, 15 - 22
Δ Vectoring.n	Change in Vectoring coverage from 2013-17 in Near area	T_E	9, 13, 15 - 18, 20 - 22
HFC.13.r	HFC coverage in 2013 in Remote area	T_E	9, 13, 15 - 18, 20 - 22
HFC.13.n	HFC coverage in 2013 in Near area	T_E	9, 13, 15 - 18, 20 - 22
HFC.Exp.r	Dummy, whether HFC coverage changed (1) from 2013-17 in Remote area	T_E	9, 13, 15 - 17
HFC.Exp.n	Dummy, whether HFC coverage changed (1) from 2013-17 in Near area	T	15
Δ HFC.r	Change in HFC coverage from 2013-17 in Remote area	T	15
Δ HFC.n	Change in HFC coverage from 2013-17 in Near area	T	15
HVT.count	Amount of MDF in a municipality	$T, (X)$	7, 14, 15, 18, 20 - 22
HVT.dens.geo	Density of MDF based on Area (in MDF per km^2)	T	20
nearby10k	Dummy, whether a neighboring municipality within 10km is accessed with FttP (1) by the end of 2013	$T_E, (X)$	9, 13, 15 - 17, 18, 20, 21
Market size (Y)			
Houses	Absolute number of residential houses	Y	15, 18, 20 - 22
Population	Absolute number of inhabitants (in 10.000)	Y	7, 14, 15, 18, 20 - 22
Age	Average age of a municipality's population (in years)	Y_E, Y_I	9, 10, 13, 15 - 22
Income p capita	Average income per inhabitant (in 1.000 Euro)	Y_I	9, 10, 15, 18 - 22
Accessibility (X)			
Density	Population density (in 100 inhabitants per km^2)	X_E, X_I	7, 9, 10, 13 - 22
Single-Family Houses	Share of one-family housing, relative to all residential houses	X	15, 18, 20 - 22
New Construction	Share of newly built residential housing, relative to all residential houses	X_E, X_I	9, 10, 13, 15 - 22
Area	Area of a municipality (in 10 km^2)	X_E, X_I	9, 10, 13, 15 - 22
Forest Area	Forest area of a municipality (in 1 km^2)	X	15, 18, 20 - 22
Industrial Area	Industrially used area of a municipality (in 1 km^2)	X	15, 18 - 22
Ruggedness	Topographic heterogeneity, defined as differences in elevation (in 100m)	X_E, X_I	9, 10, 13, 15 - 21
Min_MZ	Distance to the nearest *Mittelzentrum* (mid-sized town) in driving time (10 min. steps)	X_E	9, 13, 15 - 22
Min_A	Distance to the nearest *Autobahn* access in driving time (1 min. steps)	X	15, 22
Subsidies (S)			
Subsidies	Accumulated municipality-specific subsidy payments of the federal and Bavarian programs	S_E	15
Funding until 15	Accumulated subsidy payments received through the Bavarian program until 2015	S_E, S_I	13, 22

Notes: This table summarizes all used variables for the estimations and analyses. Descriptions and unit of measurement are provided in the second column. The third column links the variable to its category and to its sub-categories in the main specifications. Column four lists all tables detailing analyses in which the respective variable has been used.

Acknowledgments

We are grateful to Klaus Gugler, Susanne Steffes, Frank Verboven, participants at the DICE Research Workshop and the 4th DICE Winter School of applied Microeconomics and one anonymous reviewer for helpful comments and suggestions and the DFG GRK 1974 for financial support.

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Declaration of Contribution

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

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

Signature of the co-author:

Niklas Fourberg

Chapter 3

Competition on the Fast Lane - The Price Structure of Homogeneous Retail Gasoline Stations

3.1 Introduction

Road transport remains the backbone of travel and logistics, accounting for three quarters of all passenger transports and over half of all freight transport within OECD countries (OECD, 2020a,b) in 2018. Consequently, the need and cost of refuelling road vehicles is an ubiquitous necessity - and annoyance - for both private and business drivers as well as a substantial cost factor for cargo transport.

For the same reasons, fuel pricing and possible anti-competitive acts within the sector remain both in the public's eye and under investigation by economists and cartel agencies. While this interest has generated a series of regulations from enhanced transparency in Germany over limitations to price increases in Australia and Austria to outright price regulations in Belgium (Boehnke, 2017, Bundesministerium für Wirtschaft und Energie, 2018, de Roos and Katayama, 2013), the underlying questions of the level competition among retail stations and its determinants remain open for discussion.

This analysis contributes to this discussion by utilising the special case of *Bundesautobahntankstellen* in the German market, which are regulated to have identical business hours, side products and services and which are accessible only from the *Autobahn* highway network. This allows isolating the competitive interactions between stations from their side-business and also integrating a reliable demand proxy, the traffic at the respective strip of highway. In effect, the stations are thus restricted to competing on price and their fixed location with regard to customers. Additionally, car parks (*Autohöfe*), which are accessible by street and highway alike, but regulated to the same standards as *Bundesautobahntankstellen* otherwise, are used to gauge cross-network competitive effects.

Germany is well-suited for such an analysis for a number of reasons. Its *Markttransparenzstelle* and the *Bundesanstalt für Straßenwesen* provide detailed, publicly available data on highway traffic and station prices. Germany also has the fourth-most freight and the second-most passenger transport of all OECD members on its roads (OECD, 2020a,b), as its population is highly motorised and because of its position as a transit country at the heart of the European Union.[1]

Using price data of 428 *Bundesautobahntankstellen* and *Autohöfe* as well as traffic information for all of 2018, price setting and competition are analysed in accordance with the Edgeworth cycle model commonly used in the analysis of retail gasoline prices. Therein, prices are raised rarely, but steeply and jointly by most players, and reduced sequentially in smaller, more numerous and disjointed steps. This is modelled accordingly by considering price increases and decreases separately for both the decision to change and the volume of any given change. In both steps, these decisions are related to demand and its dynamic in the period of question as well as the behaviour of local competitors.

The results contribute specifically to the ongoing discussion on the collusive or competitive nature of Edgeworth cycling by providing support for the latter hypothesis: Cycling is initiated as traffic increases and ceases only as demand decreases again in the evening. Rising demand also increases the likelihood for price reductions more than for increases, while symmetrically affecting the volume of these changes. Hence,

[1] Transport volume is measured in millions passenger-kilometres and million ton-kilometres.

the chance for lower prices increases with demand. In the same competitive vein, *Bundesautobahntankstellen* respond to the pricing decisions of their local competitors despite their privileged location. They mirror price changes by stations of the same type to a large degree and to a smaller degree for similar *Autohof*-type stations, regardless of the price direction.

The remainder of the paper begins with an overview of the related and relevant literature in section 3.2, followed by an introduction into the network and thus the identification in section 3.3. In section 3.4, the data and its composition are introduced, followed by the empirical strategy in section 3.5 and the results in section 3.6. The paper concludes with a summarising evaluation of the results in section 3.7.

3.2 Literature

This paper is firmly routed in the literature on gasoline retail prices and the examination of the extensive data from German retail stations gathered by the *Markttransparenzstelle - Kraftstoffe* in particular. It contributes to this field in two related ways: First, by focussing on the role of demand for the pricing behaviour of retail stations, and second, by exploring the impact of more geographically dispersed competition in an otherwise densely populated market. Both of these are achieved by analysing a distinctive feature of the German market, the *Bundesautobahntankstellen* network, which is excluded from most other analysis of the market for the same reasons causing its usefulness here. BAT stations constitute a separate network of homogeneous stations located at pre-defined intervals and sharing the same types of customers, reducing their competitive variables to prices only. These features permit a more distinct examination of the interaction between price and demand.

The standard theory for gasoline retail pricing is the Edgeworth price cycle, based on Maskin and Tirole (1988) and introduced to fuel retail by Eckert (2002, 2003, 2004). In that model, pricing is dynamic and consists of two states: the relenting pahse and the undercutting phase. The former is, typically, a singular increase, which both follows and is followed by the undercutting phase, wherein the competitors within a market sequentially and repeatedly undercut one another with price decreases. These reductions, in theory, continue down to marginal costs and are both more frequent and significantly smaller in volume than the initial (and subsequent) increase.

Edgeworth cycling has been identified for the Canadian market (Eckert, 2002, Noel, 2007), parts of the US (Lewis, 2012), Western Australia (de Roos and Katayama, 2013), Chile (Luco, 2019), Austria (Boehnke, 2017) and Germany (Boehnke, 2017, Eibelshäuser and Sascha, 2018, Haucap *et al.*, 2017). In most of these cases, cycling is found to be an outcome of competition, with larger firms leading the relenting phases and smaller firms the undercutting (de Roos and Katayama, 2013, Lewis, 2012, Noel, 2007). Stronger competition is also associated with quicker cycles (Haucap *et al.*, 2017) and more heterogeneous firms are seen as beneficial to the existence of cycling (Eckert, 2003). This paper follows the interpretation of cycling as a competitive outcome.[2]

[2]Note that Byrne and de Roos (2019) and de Roos and Smirnov (2020) have defined conditions for which intertemporal pricing differences can be used in a collusive strategy. Under this regime, price differences and the resulting market share changes would be tolerated for a certain period of time to compel smaller market players to follow the overall collusive strategy instead of deviating further.

As stated, these studies are focused on the supply side of the market, as time-exact volume data is not accessible for researchers. At best, search data - e.g. Noel (2018), Luco (2019) - or manually collected demand data for a handful of stations - e.g. Boehnke (2017) - can be acquired to approximate demand. In other cases, consumer behaviour is found to be important but cannot be accurately traced due to the lack of data. Examples include Haucap *et al.* (2017) and Atkinson *et al.* (2014), who find that supermarket chains selling gasoline as a by-product enhance competition or Bantle *et al.* (2018) and Pennerstorfer *et al.* (2020) who find consumer routes to be important for market delineation. This paper aims to alleviate this lack of data by focussing on Germany's highway stations, which have more homogeneous customers than street stations and whose customer potential can be more accurately gauged using traffic data.[3]

Secondly, market delineation is a recurring complication in the literature. At times, restrictions of the data determine the market, as in Lewis (2012) or Noel (2007) who use cities as local markets, while in other cases like Haucap *et al.* (2017) markets are defined locally as a circle around each station or according to computational restrictions as in de Roos and Katayama (2013). Other papers specifically investigate the competitive relationship between stations so as to improve market delineation and its conditions: Bergantino *et al.* (2018) observe for Italian data that stations are spatially related, with competition spilling over across larger distances as each station affects the next, though the effect decreases with distance. Kvasnička *et al.* (2018) similarly find that station density negatively impacts prices, but decreases in effect size and significance with increasing distance. Bantle *et al.* (2018) analyse price correlations between stations to define local markets according to the stations' price interdependence and find that these relationships are driven not solely by proximity, but also and especially by commuter routes. This paper expands these delineation analyses by using highway and highway-adjacent stations, for whom commuter routes and distances are effectively identical.

3.3 *Bundesautobahntankstellen*: Network & Identification

From its conception, the German highway network, the *Autobahn*, included dedicated rest areas alongside the actual highway, the *Autobahnraststätten*, to provide necessary infrastructure for the efficient operation of the motorways. The *Raststätten* typically include restaurants, parking for cars and trucks, service areas, a hotel, and fuel stations - the *Bundesautobahntankstellen* (BAT).

Originally a state enterprise, the BAT have been privatised under the umbrella of *Tank&Rast*, but remain heavily regulated with regards to their services and the pro-

Their model hinges on inattentive consumers and price dispersion serving to further obscure prices from these consumers. Similarly, Clark and Houde (2013) have investigated a Canadian cartel case and found such a strategy to have played out in service of the cartel in question. In terms of BAT stations, this model is unlikely, because BAT stations are known to be more expensive than regular stations even during their price minima.

[3] Boehnke (2017) has also used highway traffic data to approximate demand, but matched the traffic information to street stations as well. As these can be accessed locally, too, the data loses accuracy and becomes more of a density measure.

vision thereof. The mandate includes 24 hours and seven days a week of service, but also the aforementioned restaurant and hotel areas. Truck parking and accommodation - while not a concern of the original design before the Second World War or the Fifties - have become a priority and are also required, if not expanded in cooperation with the federal government (Bundesministerium für Verkehr und Infrastruktur, 2020). Additionally, the concessions for both the *Raststätten* and their fuel stations are administrated by *Tank&Rast* (Bundeskartellamt, 2011), who sell them to independent or vertically-integrated fuel station operators, which implies a common cost for these concessions across all stations.

This similarity also applies to their location, as the federal government's guidelines - rules, prior to privatisation - define a regular distance of fifty to sixty driving kilometres between two stations; permitting a higher driving distance of eighty kilometres for areas with little long-distance traffic (Bundesministerium für Verkehr und Infrastruktur, 2020). It extends to their connection with the road network, as they can only be accessed from the *Autobahn* and only from one direction of travel[4]; a second BAT is usually built for the opposing direction.

In conclusion, BAT are, by virtue of regulation, mostly homogeneous in all relevant aspects of competition, from by-products to location and access. This makes them an ideal subject of study for price competition in general and in gasoline retail specifically, as they cannot compete with one another by any other means except their brand. Furthermore, entry is impssible except for an expansion of the BAT network by the regulator (the BMVI) and the administrator (Tank & Rast).

This suitability is increased by their relationship to their consumers. On the one hand, their location on and along the *Autobahn* potentially allows a customer to refuel without existing the highway and without having to search for a station outside of the BAT network, saving him time. On the other hand, BAT typically charge significantly higher prices than standard road stations, which could be seen as the operators' premium for the customer's saved time, but is more likely a result of their contracts with Tank&Rast and a strategy of focussing on business travellers and truckers. Both of these groups have higher time costs and might have access to fleet cards guaranteeing them a certain rebate per liter (see Bundeskartellamt, 2011), thus rendering them less price-sensitive.[5][6] Regardless of the exact cause, the result of their higher prices must be a greater reliance on price-insensitive customers who would have no choice but to use these stations, e.g. truckers at the edge of their legally mandated rest times. Moreover, this customer base again renders the stations more homogeneous, further reducing their strategic options outside of price competition.

At the same time, these characteristics lower the overall intensity of competition. The stations are placed fifty kilometres apart and designed as a local quasi-monopoly on the BAT network - notably reflected in their higher prices. Their locations and characteristics are fixed, new entry is mostly impossible and they target a price-insensitive

[4]The only exception is a local access road for delivery of the station's own supply and fuel, which may not be used by other private vehicles.

[5]Fleet cards are usually billed directly to the employer, which causes a principal-agent-problem further reducing employee incentives to search for a cheaper alternative.

[6]The extended service hours or low fuel reserves following traffic jams might also guide consumers towards refuelling at BAT.

customer base. However, the consequence of these restrictions is this: if even these stations competed, other types of fuel stations could only be more likely to do so.

More importantly, their similarity allows to investigate a comparatively pure case of price competition. Aiding in that identification is another unique feature of the BAT station network: the ability to more accurately approximate and include demand in the analysis. Traffic on the German *Autobahn* is counted by a set of 1124 counting stations operated by the *Bundesamt für Straßenwesen* (BAST) on the *Autobahn* for active traffic management and analysis purposes. These data differentiates vehicle types and is provided on an hourly basis, permitting a detailed tracing of all traffic at a given BAT station. This traffic must contain all customers of the BAT because it cannot be accessed any other way. Since the customers are more homogeneous due to the higher price levels disincentivizing all but the most price-insensitive customers, these flows should include a similar share of potential customers across the entire network. Thanks to the traffic data matching demand flows for BAT stations, the effect of demand on price can be evaluated more accurately and price competition observed more clearly.

Lastly, the only equivalent alternative to BAT stations, the *Autohöfe* (AH) can be used to measure price competition more accurately and across networks. AH stations are subject to similar regulations as BAT stations: around the clock service, sanitary installations, ample parking space for trucks and a maximum distance to the nearest highway access of one kilometre at the most (VwV-StVO (2017), Zu Zeichen 448.1). If they fulfil these conditions, they may be advertised on road signs, as BAT stations are, too. Therefore, they are the closest possible competitors and a viable alternative to trucks and business customers with a low price-sensitivity compared to their time-sensitivity. This potential is highlighted by the fact that AH stations are located on the regular road network and thus have to compete with road stations which charge significantly lower prices than BAT stations.

While their entrance can, unfortunately, not be observed, they are still a competitor intruding upon the tightly regulated and static competitive structures of BAT stations. Since they operate under a different demand and competitive structure, but are comparable in service to BAT stations, they are likely to provide competitive pressure on BAT, which will be analysed in this study to evaluate the level of competition amongst BAT and the response of fuel stations to an aggressive, lower-priced competitor.

In summary, BAT provide a set of around 340 relatively homogeneous stations with distinct, exogenous locations and a type-specific customer flow limited to a single access point, a BAT's *Autobahn* exit. These BAT stations differ significantly only in three dimensions along the *Autobahn* network: Traffic flow at their location, operator brand and the number of competitors, especially AH, in the vicinity. All of these dimensions can be controlled for, which permits observation of approximately pure price competition between these stations.

3.4 The Data

The data stems from two distinct sources, fuel station data from *Tankerkönig UG*, as received from the *Markttransparenzstelle für Kraftstoffe* (MTS-K), and traffic data from the *Bundesanstalt für Straßenwesen* (BAST). Additionally, information on infrastructure and distances was generated using Google and OSRM tools and sources. In the following section, the operations and resulting variables as well as their use will be summarised.

3.4.1 Traffic Data

Table 3.1: Summary Statistics for Traffic at BAT stations

Competing AH	Count	Unique Zst	$\mu(Pkw)$	$\sigma(Pkw)$	$\mu(Lkw)$	$\sigma(Lkw)$
No	91	52	1216	1051	201	186
Yes	212	118	1095	879	247	191

Notes: The table displays sample means and standard deviations for the hourly traffic at BAT stations with and without competing AH stations as measured by the nearest counting stations (Zst) to their location. Traffic is measured in single vehicles.

In 2018, the most recent year for which data is available, the BAST operated 1124 counting positions, called *Zählstellen* (Zst), on the *Autobahn.* These Zst are automatic installations, either radar-, light- or induction-based, and provide a detailed, hourly summary of the traffic passing their location in both directions. Since Zst are meant to serve traffic flow analyses and as input for traffic management systems, they are typically located in relative proximity to highway junctions or exits, measuring the traffic on the stretch of highway before the junction. They can differentiate between up to nine different types of vehicle, including trucks and various types of cars. However, a significant number of Zst only collects data on trucks and all traffic (Bundesanstalt für Straßenwesen, 2020), restricting the analysis to these broader categories to avoid a loss of observations. Their geographic coordinates are also provided and used in this analysis to match BAT and AH stations to the closest Zst on the same Autobahn.

For this analysis, hourly data on the number of trucks (Lkw) and all other vehicles (Kfz) passing a given station in its direction of travel are used. Trucks are therein defined as trucks with or without trailers, but of at least 3.5 tons of weight; buses are also included in this measure. Thus, the variable includes all vehicle types that (almost) exclusively use diesel fuels and should influence prices directly for that fuel type only. *Kfz* on the other hand are defined as all cars with and without trailers, delivery vehicles and motorcycles as well as unclassified vehicles. They may use gasoline (E5) or diesel and should thus be a price determinant for both fuel types.

3.4.2 Fuel Station Data

The *Tankerkönig* fuel station data encompasses the identities, locations and prices of all fuel stations in Germany since the creation of the MTS-K. Of these around 15,000

Table 3.2: Average Prices and Competitive Position per Station Type

Prices:

	Competitors			P_{Type}		$N(\Delta P)$			
Type	AH	BAT	Count	E5	Diesel	E5	Diesel		
BAT	No	Yes	90	1.59	1.44	1.2	1.2		
BAT	Yes	Yes	211	1.61	1.47	1.2	1.2		
AH	No	Yes	10	1.47	1.3	1.6	1.6		
AH	Yes	Yes	88	1.47	1.31	1.6	1.6		
Location:									
	Competitors			No. of Competitors		Avg. Distance to:		Avg. Time to:	
Type	AH	BAT	Count	AH	BAT	AH	BAT	AH	BAT
BAT	No	Yes	90	0	7.67	-	45.87	-	31.14
BAT	Yes	Yes	211	2.98	5.96	41.17	42.96	27.37	28.35
AH	No	Yes	10	0	4.7	-	36.52	-	22.7
AH	Yes	Yes	88	3.57	6.91	40.11	41.46	26.22	26.19

Notes: The first table displays the yearly average of the hourly station prices and the hourly price changes of that station type. The second table displays the competitive situation of that station by listing the number of competitors per type, the average distance to these competitors and the average driving time required to reach them. Stations are divided into BAT and AH stations, with both categories subdivided depending on whether they have to compete with (other) AH and BAT stations.

stations, 303 can be identified as BAT and 102 as AH.[7] For these stations, the dataset is restricted to observations from 2018, so as to fit the traffic data[8] and a further 21 stations have to be dropped as observation units due to a lack of suitable Zst[9]. These 21 stations are still used for competitor price calculations, since these do not require traffic information and dropping them would constitute a source of bias. Two additional BAT and four AH cannot be used in the main analysis as they lack BAT competitors; their summary statistics are displayed in Table 3.6 of the appendix.

For these competitor prices, a local market is defined around each BAT and AH station. This market is computed to include every other BAT or AH station within a linear distance of fifty kilometres, which reflects the guideline for BAT stations and consumer behavior in that use of BAT implies a time constraint, which would prohibit a long trip towards an alternative station. In a second step, all potential competitors located on a *Autobahn* running parallel to that of the station in question are dropped from the set of competitors, as drivers are unlikely to switch between parallel highways given the detour required.[10] For all remaining competitors - twelve on average -, driving

[7] Several stations cannot be identified or need to be dropped due to construction works at their location blocking access, them not having been opened within the observation period or issues with their reported prices. For AH stations, further concerns are undue distances to the *Autobahn* or insufficient truck parking space.

[8] Note that Zst are being added every year, whereas some are inoperable in certain years due to construction activity on the regular lanes. This restriction to the quality of fit between Zst and BAT stations impedes covering more than one year in the analysis.

[9] A Zst must be on the same highway and at most 50 kilometres distant from a fuel station to be considered suitable. On its 13,000 kilometres of *Autobahn* track, the network contains 213 junctions and 885 exits, corresponding to, on average, one change to traffic flows every twelve kilometres. Thus, a distance of more than fifty kilometres is already quite high.

[10] Specifically, German *Autobahnen* follow either a North-South or an East-West trajectory, with

distances and driving times to the observation unit station are calculated[11]. These yield an average distance of 47 kilometres and an average maximum distance of 76 kilometres, which fits both the aforementioned guideline and its relaxation to - at most - eighty kilometres for areas with low traffic. Driving times are 31.5 minutes on average, with an average maximum of 49.5 minutes.

Using these distances, a weighted average of competitor prices is calculated to express market price pressure on the station in question.[12] These averages and the prices for the observation unit station are calculated as hourly averages for alignment with the traffic data. Whenever price data for the observed station or any of its competitors is missing, that hour drops out. The MTS-K provides all price changes with an exact time stamp in seconds, which is used to calculate a duration-weighted price for every hour in 2018. All of these calculations are conducted for both diesel and e5 gasoline. Table 3.2 provides an overview over the average station prices and competitive characteristics for AH and BAT stations with and without AH competitors. This comparison also displays the price spread between BAT and AH stations assumed in section 3.3.

3.4.3 Other Data

Aside from station and traffic data, information on official holidays, weekends and vacations within Germany and its federal states is used to account for potential one-off effects on pricing. *Holidays* include one dummy each for federal and state-level official holidays, which are separated to account for the difference in scale associated with a federal holiday. *Weekends* are divided into Saturday and Sunday, as both days will see reduced business travel, but Sunday also nearly prohibits truck traffic, which might change pricing behaviour at these days altogether. *Vacations* adds two dummies indicating the official start and end dates of the summer holidays in the federal state in question, both of which are defined as the actual date plus the two preceding and the two following days. This definition is chosen to account for the weekends often adjacent to the vacation start states, while the variable itself is included to account for the large waves of vacation trips starting and returning at the first and last days of the holidays, respectively.[13]

Lastly, data on diesel and e5 wholesale prices are included to account for macro-economic trends and potential oil price shocks. The underlying data is the daily FOB price from the Rotterdam spot market, as provided by OMJ, which is a price benchmark for the European market and thus sufficient to serve as a control for larger trends and shocks.

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the former designated with odd numbers and the latter designated with even ones. Using these designations, all potential competitors on even-numbered *Autobahnen* are removed from the competitor set if the station in question is also along an even-numbered route. Stations along the same *Autobahn* are not dropped.

[11] The *Autobahnen* and driving directions are not extracted from the MTS-K data, but were generated by linking station locations to the nearest highways using OSRM tools and extrapolating the directions from station orientation to that highway.

[12] A simple, unweighted average is also calculated for robustness.

[13] The Easter holidays - associated with price hikes in German popular opinion - included via the Easter vacations. The start and end points of the summer vacations are included because of the large vacation-based traffic jams they typically cause, which might induce price regime changes.

3.5 The Model

Using *Autobahntankstellen* (BAT) and *Autohöfe* (AH) to abstract from non-fuel activities and thus observe price competition for homogeneous goods among highly homogeneous stations, the empirical strategy addresses three consecutive questions. First, which are the overall, static determinants of competition between homogeneous fuel stations? Second, in what manner does demand, measured by traffic as a proxy, impact competition and price-setting, and what is the effect of the composition of that competition? The third question also addresses the distinction between BAT and all other stations, as originally defined by the *Bundeskartellamt*. For the first question, station characteristics and prices at a specific hour of the week are assessed. The interaction between demand, competition and prices is investigated using hourly data of the binary decision to change prices and the volume of a price change, if executed.

3.5.1 Static Determinants of BAT & AH Station Prices

The variable of interest in the static analysis are the price for *Super E5* gasoline and diesel, respectively, at a specific hour and day of every week in the year 2018. Specifically, the main analysis uses prices at Monday, 08:00 o'clock, while afternoon and weekend price moments are displayed in the appendix.[14] This choice allows comparison and identification of pricing determinants and regimes at a time of relatively high traffic - i.e. the commute to work. Given the restrictions of the approach, this identification serves primarily to test the assumptions made in section 3.3 and as support for the specifications used in the dynamic analysis. Price relationships, for example, are affected by homogeneous input costs, overstating their intensity in this static perspective.[15]

Stations are subdivided into three types: AH stations, BAT stations with AH competitors, and BAT stations competing only with other BAT. Price levels for the stations of each type are compared to the price levels of their intra-type and, if applicable, extra-type competitors. The hypothesis is that the price response increases with competitive pressure: lowest for BAT stations without AH competition and highest for AH stations, which have to compete with normal road stations also. The number of prices of BAT and AH competitors in the given hour is also included to account for price regime effects related to Edgeworth cycling, i.e. faster cycles leading to lower minimum prices[16] and higher volatility. Both the price level and the number of changes are summarised as *CptD*, the dynamic competition effects.

The competitive structure is further gauged by including static competition effects (*CptS*). These are the average travel time from one station to its local competitors, the number of competitors (of both types) and brand dummies covering the four oil majors on one side and the smaller market participants as *Other* brands on the other

[14] See Table 3.7 and Table 3.8.

[15] The non-stationarity of the data, which necessitates the use of first differences in the dynamic analysis to avoid bias, might also remain an issue despite the choice of a specific point in time to avoid it.

[16] Siekmann (2017) has observed this pro-competitive effect of cycling in his supply-side analysis of the German street stations.

side.[17] The number of competitors notably does include other stations of the same brand. The reasoning behind this decision is twofold. First, while brands can theoretically coordinate prices for their stations, these stations are still exchangable from a consumer's perspective if they were to offer lower prices or benefit his route planning. Second, if a brand operates more than one station in a market, these stations are seen as different competitors by stations of other brands.

The models for the three station types and the fuel types $F = [E5, Diesel]$ are defined as:

$$P^F_{AH} = c + CptD^F_{BAT}\beta + CptD^F_{AH}\gamma + CptS^F_{BAT}\delta + CptS^F_{AH}\zeta + \text{brand}\zeta \quad (3.1)$$
$$P^F_{BAT} = c + CptD^F_{BAT}\beta + CptD^F_{AH}\gamma + CptS^F_{BAT}\delta + CptS^F_{AH}\zeta + \text{brand}\zeta \quad (3.2)$$
$$P^F_{BAT_{AH.comp}} = c + CptD^F_{BAT}\beta + CptD^F_{AH}\gamma + CptS^F_{BAT}\delta + CptS^F_{AH}\zeta + \text{brand}\zeta \quad (3.3)$$

3.5.2 Determinants of Price Changes

Expanding on the static analysis, dynamic pricing behavior is analysed first by observing changes in station prices and regressing them on demand and competitor pricing. Pricing decisions are split into increases (relenting) and decreases (undercutting). This choice is modelled after the Edgeworth model for gasoline prices, wherein relenting phases are rarer and steeper than the steps of the undercutting phase and thus would plausibly result from different considerations. The decisions are further split into *E5* and *diesel*, the two most common fuels in Germany, because the latter is more regularly used for business travellers and almost exclusively for trucks. The control variables include wholesale costs (Δc^{E5}_{it}) and potential demand (d_{it})). The latter includes the present car and truck traffic as well as their trends, which are included to account for differences in responding to rising and falling traffic and defined as follows.

$$\Delta d^{Type} = \frac{(d_t - d_{t-1})}{\sigma d}, \qquad \text{Type} = [Pkw, Lkw]$$

Information on BAT competitor pricing behaviour ($\Delta cptD_{id}$) is included by their distance-weighted average price and a dummy evaluating whether they changed prices or not. The same information is included for AH competitors ($\Delta cptDAH_{id}$), provided that at least one AH station is sufficiently close. This definition is summarized in Equation 3.4 and follows from the use of fixed effects, which capture the existence of competitors already, leaving only the interaction for analysis. This inclusion serves to expand the analysis beyond the centrally-planned structure of BAT.

While AH cannot be considered a treatment of entirely exogenous shock, since their entry is not observed, they are still an intrusion into the BAT system, permitting customers - including truck drivers - to eschew BAT for AH stations. Moreover, BAT stations cannot adjust their location in response to this competition, while AH location is based primarily on truck traffic, which provides their main revenues through night stops and maintenance. Their impact on BAT competition is therefore not their

[17] For robustness, the competitive measures were augmented by a measure of brand density, the share of competing stations belonging to the same brand as the observed station, and by dividing the number of competitors into types. Neither changed the results.

primary intent, but meaningful to gauge the intensity of competition across networks, i.e. when the customer has to divert from his route to benefit from a lower price.

$$p^{w\_avg,AH} = \begin{cases} 0 & if AH.comp = 0 \\ p^{w\_avg,AH} & if AH.comp = 1 \end{cases} \tag{3.4}$$

For the price variables, first differences are used instead of levels for three reasons. First, prices are relatively homogeneous across stations due to them being dependent on common supply factors, which would inflate coefficients. Second, prices are non-stationary due to this dependence, which would bias results if left unaddressed. Third, as stations can only compete with one another by adjusting prices, the change in price is the variable of interest for gauging competitive pressure.

Hence, the analysis observes the determinants of the linearised probability for a price change in a given hour, using first differences of all price (*cptD*) variables. Present demand (*d*) variables are included in level, because the relevant information for price-setting is the amount of potential consumers at a given point in time. Station fixed effects (α) are included to capture remaining location and station anomalies - e.g. construction measures restricting access, location near a national border - and abstract away from static components analysed in the first step. The resulting models are estimated using OLS with robust standard errors following Arellano's 1987 method.[18] They are defined as follows for both fuel types $F = [E5, Diesel]$:

$$Prob(P^F > 0|c, d, D, \alpha) = f(\Delta c_{it}^F \beta, d_{it}^F \gamma, \Delta cptD_{it}^F \zeta, \Delta cptDAH_{it}^F \theta, \alpha_i) \tag{3.5}$$
$$Prob(P^F < 0|c, d, D, \alpha) = f(\Delta c_{it}^F \beta, d_{it}^F \gamma, \Delta cptD_{it}^F \zeta, \Delta cptDAH_{it}^F \theta, \alpha_i) \tag{3.6}$$

These models are also estimated for AH stations to analyse divergences from BAT in their competitive structure. In both cases, it is assumed that rising demand should cause an undercutting phase as the potential gain from undercutting competitor's prices is increased; and vice versa. For competitor prices, a consistently positive relationship is assumed.

3.5.3 The Volume of Price Changes

Once the decision to change prices is made, the question of the volume of that change needs to be addressed. The determinants of this second decision are modelled in this second stage. Analogous to the previous approach, relending relenting and undercutting are analysed separately. This also better reflects the Edgeworth model assumptions, in that relenting phases are typically much higher in volume than undercutting moves.

[18]Note that OLS is used instead of a Probit or Logit model because the simultaneity of price moves in the market and the inclusion of fixed effects prevents the algorithm from converging. An exclusion of competitors' price moves is, however, impossible as it would bias results while using lagged price changes would be a mis-specification due to the fast-moving nature of the German retail gasoline market. Hence, OLS is more robust and accurate despite the risk of expected probabilities with values above 1.

The model is defined using the same categories as the equation from subsection 3.5.2, but swaps competitors' decision to change prices with the average number of their hourly price changes. It also includes a binary variable for large price changes by AH stations defined as $|\overline{\Delta P_{AH}^F}| \upuparrows = |\overline{\Delta P_{AH}^F}| > \sigma_{\Delta p_{it}^F \neq 0}$, i.e. a price change of above one standard deviation of BAT stations' price changes.[19] According to empirical findings on Edgeworth cycles in gasoline retail, faster cycles would be associated with higher competitive pressure, more price changes and thus, potentially, lower prices, which is why the variable is added. As before, BAT and AH competitors are included separately. Wholesale prices are excluded because they are set daily and therefore unlikely to influence intra-day pricing behaviour outside of the first response when wholesale markets open. Aside from these alterations, the models are identical, and the volume equations are defined as follows:

$$\Delta p_{it}^F = d_{it}\gamma + \Delta cptD_{it}^F\zeta + \Delta cptDAH_{it}^F\theta + \alpha_i, \qquad \text{F} = [\text{E5, Diesel}] \tag{3.7}$$

3.6 Results

3.6.1 Static

The static analysis in Table 3.3 provides support for the assumption of three separate price regimes for the three station types. On the one hand, AH stations, which are on the standard road network and have to compete there as well, match their AH competitor's prices by about 94 percent for both fuel types.[20] Their prices are related to BAT competition as well, but weakly at 4 cent for every euro of the average of the competitors' prices and only at the 10% significance level.

On the other hand, BAT stations facing only intra-type competition match the prices of these competitors by 40 cent per euro and liter for gasoline and by 51.45 cent for diesel. This differences hints at the assumed competitive relationships, but is not statistically significant. Meanwhile, BAT stations facing both types of competitors react symmetrically. Regardless of fuel or competitor type, they raise their prices by 30 cent for every euro of the competitors' prices. Of all three station types, only BAT stations without AH competition respond to the number of price changes by their competitors. For every additional change by their intra-type competitors, they reduce their prices by 2.2 to 2.5 cent.

In contrast, The coefficients for wholesale prices appear small at 1.23 cent for gasoline and 2.83 for diesel per additional 100\$/t. However, this effect is likely understated due to the correlation between retail and wholesale prices, but also reflects contracts and insurances against price volatility by station operators.

These results support several assumptions regarding the identification. First, AH stations do not appear to view BAT stations as their primary competitors, yet BAT stations operate a different pricing regime when facing AH competition. Secondly, the static location parameters (i.e. distance to competitors and number thereof) are

[19] This corresponds to a change of at least 4.7 cent for E5 gasoline and at least 4.97 cent for diesel.

[20] To be precise, for every euro of the distance-weighted average price of their competitors, the given station's prices increases by almost 94 cent.

Table 3.3: Static Analysis of BAT & AH Station Price Determinants: Monday, 08:00 - 09:00 AM

	Endog. Var	Price in Level					
	Fuel Type	E5 gasoline			Diesel		
	Station Type	AH	BAT		AH	BAT	
	Comp. Types	AH, BAT	BAT	BAT, AH	AH, BAT	BAT	BAT, AH
Wholesale	(Intercept)	4.70^{*}	91.40^{***}	56.83^{***}	4.50^{*}	56.78^{***}	42.47^{***}
		(2.38)	(25.07)	(10.41)	(2.10)	(16.95)	(8.94)
	FOB_E5	0.14	1.23^{**}	0.69			
		(0.10)	(0.42)	(0.58)			
	FOB_Diesel				0.36^{*}	2.83^{**}	1.28
					(0.17)	(1.00)	(0.86)
BAT Comp.	$\overline{P_{BAT}^{E5}}$	$3.47^{\cdot}$	40.04^{*}	32.25^{**}			
		(1.92)	(17.65)	(10.21)			
	$\overline{N(P_{BAT}^{E5})}$	-0.47	-2.21^{***}	-0.52			
		(0.36)	(0.62)	(0.42)			
	$\overline{P_{BAT}^{Diesel}}$				$3.68^{\cdot}$	51.45^{**}	33.21^{***}
					(1.98)	(16.44)	(9.61)
	$\overline{N(P_{BAT}^{Diesel})}$				-0.53	-2.51^{***}	-0.68
					(0.41)	(0.64)	(0.47)
AH Comp.	$\overline{P_{AH}^{E5}}$	93.40^{***}		31.74^{***}			
		(1.59)		(5.59)			
	$\overline{N(P_{AH}^{E5})}$	0.16		0.10			
		(0.14)		(0.26)			
	$\overline{P_{AH}^{Diesel}}$				92.79^{***}		35.20^{***}
					(1.99)		(7.66)
	$\overline{N(P_{AH}^{Diesel})}$				-0.09		0.13
					(0.15)		(0.30)
Location	Time to BAT	0.00	0.09	-0.06	-0.04	0.07	-0.05
		(0.03)	(0.06)	(0.08)	(0.04)	(0.07)	(0.08)
	Time to AH	0.02		0.08	0.02		0.07
		(0.02)		(0.05)	(0.02)		(0.05)
	No. of Comp.	-0.00	0.04	0.22	0.03	0.04	0.24
		(0.05)	(0.08)	(0.14)	(0.06)	(0.08)	(0.15)
Brand	Other	$-0.94^{\cdot}$	-7.56^{***}	-3.17^{*}	-1.31^{*}	-8.43^{***}	-3.43^{*}
		(0.55)	(2.19)	(1.61)	(0.64)	(2.20)	(1.62)
	ESSO	-2.58^{***}	$-2.67^{\cdot}$	-1.01	-2.65^{***}	$-2.64^{\cdot}$	-1.28
		(0.62)	(1.50)	(0.92)	(0.73)	(1.39)	(1.11)
	Shell	-1.37^{**}	-1.63^{*}	-1.75^{**}	-0.88	0.22	-0.31
		(0.50)	(0.72)	(0.67)	(0.58)	(0.88)	(0.86)
	TOTAL	-2.34^{***}	-4.95^{**}	-4.79^{***}	-2.81^{***}	-6.35^{***}	-6.31^{***}
		(0.49)	(1.53)	(1.25)	(0.62)	(1.64)	(1.46)
	Adj. R^2	0.86	0.43	0.21	0.88	0.58	0.29
	Num. obs.	4295	4138	10216	4295	4138	10216

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

Static Analysis for the prices of AH and BAT stations at all Mondays of 2018 for the period from 08:00 to 09:00 AM, in the latter case subdivided into those without and with AH competitors. Stations without BAT or AH competitors are excluded. The first three columns depict results for gasoline, the latter three for diesel. Average Competitor prices are provided in Euro per liter, wholesale prices as $100\$/t$. The number of average price changes by the competitors within that hour is also included. Average time to BAT or AH is the average travel time to the local competitors. Regarding the brand dummies, Aral serves as the base category because its stations have, on average, the highest prices and because it is the largest operator alongside Shell. Outside of these two, Esso and Total also have their own categories, as they are major players in the market. All other owners of BAT and AH stations are subsumed under the *Other* label. Standard errors are clustered on the station level.

non-significant given the lack of variation in them due to the network design. Thirdly, BAT stations - especially when facing only intra-type competition - appear somewhat more sensitive to competitor's diesel prices than to gasoline prices. This asymmetry is not visible for AH stations, but also not statistically significant and thus at best a preliminary interpretation. Nonetheless, these results point towards a competitive relationship, but also to barriers imposed on that competition by network design and location.[21]

Notably, the brand effects, too, attest to type-specific regimes: Their spread is highest for BAT facing only intra-type competition and lowest for AH stations. Aral - also the base category - and Shell, the two largest single operators in the set always have the highest brand premia, although Shell marginally underbids Aral for gasoline by 1.37 to 1.75 cent per liter (c.p.). Total and Esso, the other two major operators, on the other hand differentiate their premia by station type. Total underbids Aral for every station type, but the difference is twice as high for BAT stations: between 5 and 6 cent for BAT to 2 or 3 cent for AH. In the case of Esso, only its AH stations underbid Aral and Shell significantly. Minor players, subsumed under the *Other* label follow the opposite strategy to Esso and underbid strongly at their BAT stations, but weakly (to non-significant) at AH stations.

3.6.2 Price Changes

Table 3.4 depicts BAT hourly pricing decisions for the entirety of 2018. A characteristic example for the pricing process is provided in Figure 3.1. BAT operators' pricing decisions appear to be influenced by traffic, competitor behaviour, holidays and weekends (see also Table 3.9). [22]

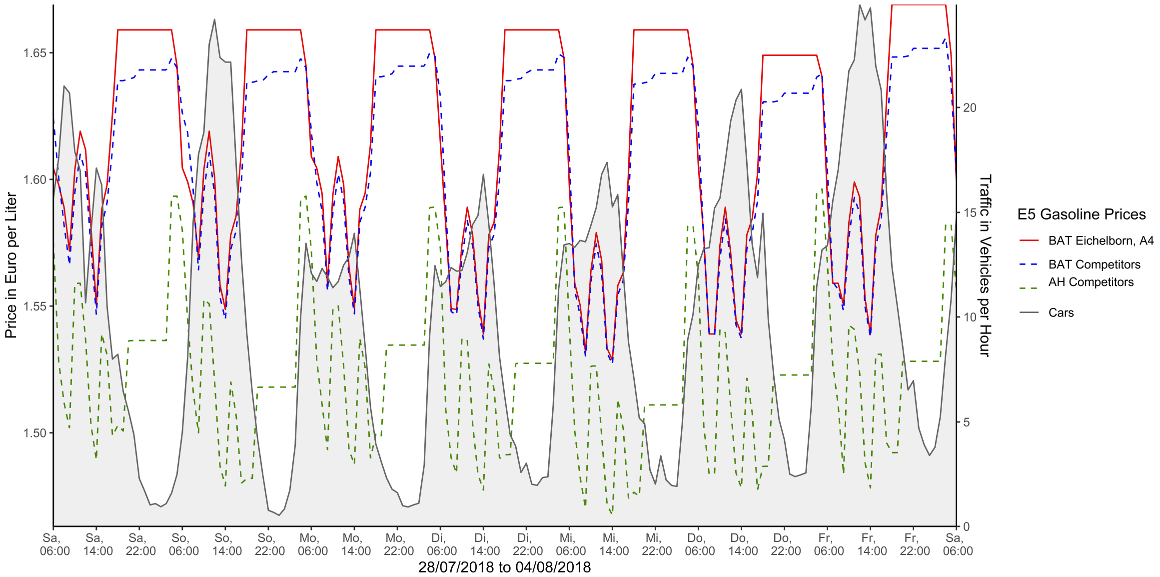
Demand Increasing demand - measured as present traffic of both trucks (*Lkw*) and all cars (*Pkw*) - is associated with higher likelihoods of price changes in both directions.[23] The relationship with undercutting is slightly stronger than that for relenting. This observation is in line with Edgeworth cycling in that higher potential demand

[21]The variation in intercept size between the fuel and station types also indicates different regimes: The constant is highest for BAT stations facing only intra-type competition and lowest for AH stations on the road network, which fits the higher price levels for BAT and their lesser exposure to competition. Similarly, the intercept is higher for gasoline than diesel, which reflects its higher price, but potentially also a stronger competition for diesel amongst the observed stations.

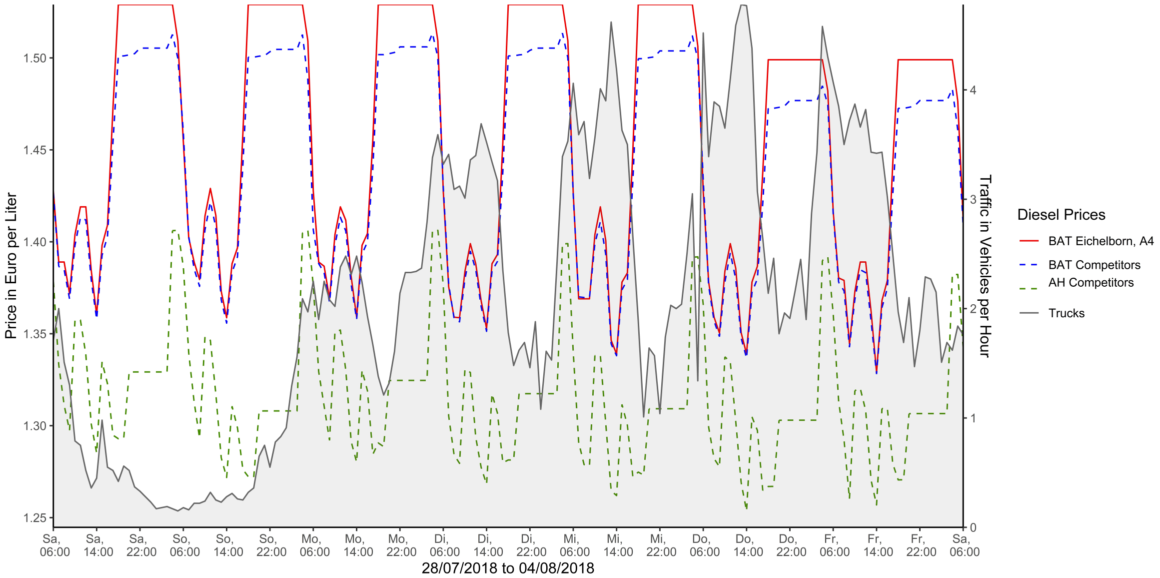
[22]Changes in the wholesale price appear to be weakly relevant for the decision to increase prices and irrelevant for intra-day price reductions. The effect is very small even when significant - a 2 percent increase in the likelihood to raise diesel prices given an (unlikely) increase of wholesale prices by 100$ per ton.It should be noted that this effect might be understated, as the wholesale prices - *free on board* prices for Rotterdam - are set daily, not hourly. Hence, their variation is by definition much lower than that of the gasoline prices, as it can only be accounted for once a day while the average station posts 7.6 prices per day. This change is defined as occurring at 09:00 o'clock, the opening of the exchange. Insurance policies and intra-company transfer prices are also not considered in this analysis.

[23]This finding is in line with Boehnke (2017) who also postulate that pricing and demand need not move in the same direction. Note also that these regressions have also been conducted using unweighted average prices instead of the distance-weighted ones used in the main specifications, but were only marginally changed by that change due to the relative homogeneity of competitor locations.

Figure 3.1: Characteristic Cycling & Traffic



Notes: This figure depicts hourly E5 gasoline prices for the period from Saturday, 28/07/2018 06:00 AM, to Saturday, 04/08/2018 06:00 AM, for the BAT station Eichelborn located along the A4 *Autobahn*. Also shown are the prices of that station's local BAT and AH competitors as well as the hourly car traffic at the station.



Notes: This figure depicts hourly diesel prices for the period from Saturday, 28/07/2018 06:00 AM, to Saturday, 04/08/2018 06:00 AM, for the BAT station Eichelborn located along the A4 *Autobahn*. Also shown are the prices of that station's local BAT and AH competitors as well as the hourly truck traffic at the station.

Table 3.4: Determinants of Price Change Decisions

	Endog. Var	$Prob(P^F > 0)$		$Prob(P^F < 0)$	
	Fuel Type	E5 Gasoline	Diesel	E5 Gasoline	Diesel
Demand	Pkw	0.003^{***}	0.003^{***}	0.003^{***}	0.003^{***}
		(0.000)	(0.000)	(0.000)	(0.000)
	Lkw	0.005^{***}	0.006^{***}	0.012^{***}	0.012^{***}
		(0.001)	(0.001)	(0.001)	(0.001)
	ΔPkw	-0.037^{***}	-0.037^{***}	-0.023^{***}	-0.024^{***}
		(0.007)	(0.007)	(0.005)	(0.005)
	ΔLkw	-0.008^{*}	-0.008^{*}	-0.016^{***}	-0.013^{**}
		(0.004)	(0.004)	(0.004)	(0.005)
BAT Comp.	$\overline{\Delta P^{E5}_{BAT}}$	0.032^{***}		-0.025^{***}	
		(0.002)		(0.002)	
	$\Delta P^{E5}_{BAT} > 0$	0.233^{***}			
		(0.011)			
	$\Delta P^{E5}_{BAT} < 0$			0.223^{***}	
				(0.011)	
	$\overline{\Delta P^{Diesel}_{BAT}}$		0.029^{***}		-0.023^{***}
			(0.002)		(0.002)
	$\Delta P^{Diesel}_{BAT} > 0$		0.240^{***}		
			(0.011)		
	$\Delta P^{Diesel}_{BAT} < 0$				0.232^{***}
					(0.012)
AH Comp.	$\overline{\Delta P^{E5}_{AH}}$	0.000		-0.005^{***}	
		(0.001)		(0.001)	
	$\Delta P^{E5}_{AH} > 0$	0.051^{***}			
		(0.010)			
	$\Delta P^{E5}_{AH} < 0$			0.056^{***}	
				(0.008)	
	$\overline{\Delta P^{Diesel}_{AH}}$		-0.000		-0.005^{***}
			(0.001)		(0.001)
	$\Delta P^{Diesel}_{AH} > 0$		0.053^{***}		
			(0.010)		
	$\Delta P^{Diesel}_{AH} < 0$				0.057^{***}
					(0.008)
Dummies	Wholesale Δ	yes	yes	yes	yes
	Station-FE	yes	yes	yes	yes
	Vacation	yes	yes	yes	yes
	Holiday	yes	yes	yes	yes
	Weekend	yes	yes	yes	yes
	Adj. R^2	0.201	0.200	0.209	0.217
	Num. obs.	2,410,109	2,410,109	2,410,109	2,410,109

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

Analysis of the determinants of hourly price change decisions for all BAT stations in 2018. Standard errors are corrected for autocorrelation and heteroskedasticity using Arellano's method with clustering on the station level. Hence, the R^2 is not informative. Columns (1) and (2) depict the determinants of the decision to raise prices for a given station in a given hour for gasoline and diesel, respectively. Columns (3) and (4) depict the same for the decision to lower prices. The control variables include hourly truck and car traffic, in 100 vehicle steps, as well as its trend. First differences of distance-weighted competitor prices and dummy variables indicating their pricing decisions are included for each fuel and station type. Information on AH competitors must be understood as an interaction term of the variable itself and the existence of AH competitors. Holidays, the start and end of summer vacations and weekends are demarked by dummies. Fixed effects and wholesale prices in first differences are included. Results for the dummies and wholesale prices are shown in Table 3.9.

would increase the incentives of undercutting by promising a larger share of the demand. Once undercutting begins, the cycle would accelerate as competitors join in.

Specifically, for each additional 100 trucks passing a station per hour the probability to undercut increases by 1.2 percentage points for diesel. This is twice the effect size of the same increase on the likelihood of a relenting move. At the peak rush hour in the network (2280 trucks), it translates to a 25 percentage point increase. Given the relative importance of trucker demand to BAT stations, it is unsurprising that these effects are larger than those for car traffic: For every 100 vehicles, the likelihood of a price change in either direction raises by 0.3 percentage points.[24] Notably, the effects are almost identical for gasoline and diesel pricing decisions, which reflects the high correlation between the two prices and indicates that most stations and brands appear to prefer a static difference between them.[25]

The dynamic of traffic ($\Delta Pkw/Lkw$) also informs on stations' pricing behaviour, suggesting a persistence in cycling intensity. If car traffic was one standard deviation lower in the previous hour (935 cars less), the probability of relenting moves in the given hour is reduced by 3.7 percentage points and that of undercutting by 2.3 percentage points. If traffic had been higher the period before, the probability would increase by the same margin instead. The coefficients are overall lower for truck traffic, but relatively stronger for undercutting (1.3 to 1.6 percentage points) than for relenting (0.8). As undercutting is the more relevant measure for the intensity of competition, this underlines the importance of truck traffic for BAT price competition. Car - and thus commuter - traffic progression on the other hand appears to shape relenting decisions.[26]

Given that high present traffic is linked with more intense cycling and low traffic with the relative lack thereof, these results then imply that Edgeworth cycling behaviour can neither be stopped immediately when traffic declines nor does it commence immediately as traffic mounts. Instead, it is caused by ensuing competition for an increasing demand following (nightly) periods of little traffic, as can be observed for the exemplary case shown in Figure 3.1. Once cycling has intensified, this behaviour continues for as long as potential demand remains high, until traffic declines for a longer period of time, allowing pro-competitive cycling behaviour to wind down.

[24]For the maximum car traffic observed in the *Autobahn* network (6818 vehicles), this still corresponds to a 27.2 percentage point increase in the undercutting and relenting probabilities.

[25]The model was also estimated for AH stations, as displayed in Table 3.10. There, the effects for present demand are similar overall, but stronger for car traffic and undercutting. This result supports the assumption from section 3.3 that *Autohöfe* compete more with street stations and are thus more interested in car drivers than BAT stations. However, as AH stations can be accessed from the regular road network as well, the *Autobahn* traffic flows lose some of their accuracy as demand approximations when used for non-BAT stations.

[26]The results for AH stations (see Table 3.10) differ here. A steep increase in car traffic to the last period actually raises the linearised probability of price increases by 5.5 percentage points. This reflects a difference in cycling behaviour, as can be observed in Figure 3.1: BAT stations tend to steeply raise their prices in the evening, keeping them at level until commencing traffic causes them to cycle again. AH stations also raise their prices overnight, but not to the same degree. Instead, they tend to perform a larger price hike just as traffic increases again. This may be designed to extract higher profits from early commuters who cannot afford a detour. At the same time, steep increases in truck traffic reduce the probability of a price increase by 4.3 to 4.7 percent - five times the effect observed for BAT stations. This once again signals the relevance of trucker demand for the AH business model.

Competition If at least one BAT competitor to a given station changes its prices, this corresponds to a 23 to 24 percentage point increase in probability of a price change in the same direction for that station. For AH competitors, this relationship is almost five times smaller (5.1 to 5.7 percentage points), but significant. The latter result is of particular interest because AH stations compare primarily with normal road stations, not BAT, as the divergence in price levels indicates (see Table 3.2 and Figure 3.1). Thus, their pricing behaviour cannot result from simultaneous price setting, as is potentially the case amongst BAT stations.

It then implies that BAT stations have to respond to the prices of their competitors despite the large distances between them both within and without the *Autobahn* network. Since station fixed effects are included, this relationship cannot be attributed to brand affiliation, but can instead be interpreted as an attempt to avoid being undercut by too large a margin, which might otherwise affect even relatively price-insensitive customers.

This interpretation is supported by the effects for the volumes of competitors' price changes on station price setting decisions: Each cent by which competing BAT raise their gasoline (diesel) prices on average corresponds to a 3.2 (2.9) percentage point increase in the probability of a given station raising prices as well. For price decreases, this effect is slightly weaker at 2.5 (2.2) percentage points. If competing AH stations exist and raise prices, however, the volume by which they do so is irrelevant for the BAT response, while the volume of AH price decreases does affect BAT station responses. The likelihood to lower prices increases by 0.5 percentage points (for both fuel types). While this effect is comparably small, it is nonetheless significant and in line with the interpretation of BAT stations reacting primarily when having to avoid being undercut.

3.6.3 The Volume of Price Changes

Table 3.5 shows the determinants of the volume changes in gasoline and diesel prices, divided by fuel types and the direction of change. The changes are measured in absolute numbers and denoted in cents per liter. Again, both competitor behaviour and demand factors appear to influence the pricing decisions asymmetrically with stronger effects observed for relenting than undercutting.

Demand The effects of present demand for the volumes of these price changes are negative. That is, per 100 cars passing a station, the volume of price changes is lowered by 0.03 ct/l, regardless of the change's direction. For trucks, this effect lies between 0.05 and 0.08 cent per 100 vehicles. Given the observed positive relationship between present traffic and price change decisions, these results are in accordance with Edgeworth cycling. Therein, undercutting steps would become more numerous - as observed - and individually smaller as competition increases.

However, the relenting moves should become larger in response, which is not immediately observable, but partially linked to the dynamic of traffic. For each standard deviation by which traffic increases from the last period to the current one ($\Delta Pkw/Lkw$), relenting steps increase by 0.1 to 0.16 ct/l for all type combinations but cars and diesel. This means that larger relenting steps manifest in periods of steeply increasing traffic. However, this effect is being countermanded by the negative impact of present demand

Table 3.5: Determinants of the Absolute Volume of Price Change Decisions

	Endog. Var	$\lvert\Delta p_{it}\rvert$			
	Fuel Type	E5 Gasoline		Diesel	
	, if:	$\Delta p_{it} > 0$	$\Delta p_{it} < 0$	$\Delta p_{it} > 0$	$\Delta p_{it} < 0$
Demand	Pkw	-0.03^{***}	-0.03^{***}	-0.03^{***}	-0.03^{***}
		(0.00)	(0.00)	(0.00)	(0.00)
	Lkw	-0.05^{***}	-0.07^{***}	-0.06^{***}	-0.08^{***}
		(0.01)	(0.01)	(0.02)	(0.01)
	ΔPkw	0.12^{*}	-0.10^{**}	0.10	-0.15^{***}
		(0.05)	(0.03)	(0.06)	(0.04)
	ΔLkw	0.14^{**}	0.04	0.16^{**}	0.04
		(0.05)	(0.03)	(0.06)	(0.04)
BAT Comp.	$\overline{\Delta P^{E5}_{BAT}}$	0.65^{***}	-0.62^{***}		
		(0.04)	(0.04)		
	$N(\Delta P^{E5}_{BAT} \neq 0))$	0.25^{*}	-0.15^{***}		
		(0.10)	(0.04)		
	$\overline{\Delta P^{Diesel}_{BAT}}$			0.68^{***}	-0.65^{***}
				(0.04)	(0.04)
	$N(\Delta P^{Diesel}_{BAT} \neq 0))$			0.19	-0.18^{***}
				(0.12)	(0.04)
AH Comp.	$\overline{\Delta P^{E5}_{AH}}$	-0.03^{*}	0.01		
		(0.01)	(0.01)		
	$\lvert\overline{\Delta P^{E5}_{AH}}\rvert \upuparrows$	0.64^{***}	0.63^{***}		
		(0.07)	(0.07)		
	$N(\Delta P^{E5}_{AH} \neq 0))$	0.02	-0.04		
		(0.06)	(0.03)		
	$\overline{\Delta P^{Diesel}_{AH}}$			$-0.03^{\cdot}$	0.02
				(0.01)	(0.01)
	$\lvert\overline{\Delta P^{Diesel}_{AH}}\rvert \upuparrows$			0.60^{***}	0.71^{***}
				(0.08)	(0.09)
	$N(\Delta P^{Diesel}_{AH} \neq 0))$			-0.02	-0.03
				(0.07)	(0.03)
Dummies	Station-FE	yes	yes	yes	yes
	Vacation	yes	yes	yes	yes
	Holiday	yes	yes	yes	yes
	Weekend	yes	yes	yes	yes
	Adj. R^2	0.26	0.23	0.29	0.27
	Num. obs.	360,998	411,937	372,167	424,801

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

Analysis of the determinants of the volume of all price change decisions in 2018 for all BAT stations. Standard errors are corrected for autocorrelation and heteroskedasticity using Arellano's method with clustering on the station level, hence the R^2 is not informative. The dependent variables are the absolute cent/liter changes in E5 gasoline and diesel prices for positive - columns (1) and (3) - and negative changes - columns (2) and (4). respectively. Gasoline is shown first, diesel second. Demand variables are the hourly truck and car traffic, in 100 vehicle steps, as well as their trends. Competitor behaviour is assessed by the first differences of distance-weighted competitor prices and the number of price changes in the given hour by BAT and AH stations. Information on AH competitors must be understood as an interaction term of the data itself and the existence of AH competitors. Holidays, the start and end of summer vacations and weekends are demarked by dummies and fixed effects are included. Results for the dummies are shown in Table 3.11

on the size of relenting steps. This latter relationship also discloses the other situation in which larger price increases would occur: longer periods of extremely low traffic.[27]

Competition BAT stations strongly adhere to the price changes of their intra-type competitors. Stations match each cent of the average of their BAT competitors' changes by 0.62 to 0.68 cent in the same direction, if they also choose to change prices.[28] The number of BAT competitor's price changes, a measure of cycling intensity, has expected effects. For each additional gasoline price change competitors conduct in the given hour on average, a relenting move becomes 0.25 cent steeper and an undercutting one by 0.15 cent smaller. In the case of diesel, however, the number of changes only affect undercutting steps.

Again, these results fit a pro-competitive Edgeworth interpretation. As cycle intensity increases in the number of price changes, relenting steps become larger and undercutting ones smaller, because firms sequentially try to undercut one another. Given this, higher counts of price changes are more likely to occur in undercutting phases, which fits the non-significance of that count for diesel relenting.

The results for AH competition underscore this interpretation. If AH stations alter their prices substantially ($\overline{|\Delta P^F_{AH}|} \upuparrows$) BAT prices respond by increasing the volume of their own price alteration by 0.6 to 0.7 cent per liter. This effect is also, notably, strongest for price decreases of diesel fuels, where competition between the two station types should be highest. In the case of price increases, it is also countermanded by a small, weakly significant negative impact of the change in average AH prices, which lowers the price increase of the station in question by 0.03 cent per cent of competitor change. That is, BAT stations react to their competitors' volume changes especially when they are at risk of being undercut too substantially, but also relent alongside their competition.[29]

While a collusive interpretation based on price spreads as a means of distribution demand between stations could also be at play, it is unlikely for competition across networks. AH stations cannot select their prices according to their BAT competitors because of their location on the road network and their resulting competition with road stations for private customers. Therefore, BAT network stations could not channel sufficient demand towards AH stations as they do not compete for this non-*Autobahn* demand in the first place. For the same reason, AH stations are more likely to affect BAT pricing than for the reverse to occur. It is the BAT stations that must avoid being undercut too severely for their location advantages to prevent a demand drain.

[27] The model was also estimated for AH stations, as displayed in Table 3.12. There, the effects for demand were weaker and less significant than for BAT. This result affirms the restriction and assumption from section 3.3 that *Autobahn* traffic flows would lose their accuracy as demand approximations when used for non-BAT stations as they can be accessed by other roads as well.

[28] Theoretically, if one station opts to lower prices while competitors raise theirs, the results indicate that this decrease would be reduced by 0.62 (0.65) cent per liter gasoline (diesel) for every cent of increase by their competitors; and vice versa.

[29] The analysis of determinants for the volume of price changes for AH stations (see Table 3.12) supports this argument: AH stations respond to the price changes of intra-type competitors in a manner similar to BAT stations. Their response to BAT station price setting is, by comparison, five to ten times weaker, while the strongest reaction occurs for diesel undercutting steps. There, for every additional cent of the decrease, the AH lowers its own price by an additional 0.08 cent.

3.6.4 Discussion of Results

The relationship between a BAT station's pricing behaviour and the average prices of its direct BAT competitors cannot be understood as a causal one. While brand-specific effects, including potential intra-brand coordination, are captured in the fixed effects, a similar motion across all stations cannot be ruled out based on this analysis. The construction of average prices, necessary for inclusion of the hourly demand variables, further complicates the issue as the exact timing of the pricing decisions within a market must remain unobserved to avoid a bias with regard to demand. Hence, this analysis cannot provide insight into the identity of price leaders and followers within the BAT market. However, the positive link between the likelihoods for price reductions and intra-network undercutting do imply a pro-competitive relationship. From a station operators' point of view, keeping prices high would be the superior option if competition and undercutting could be avoided.

Hence, this analysis of BAT stations and the AH stations on the edge of the formers' network implies the existence of competition across networks and larger distances, albeit lessened by either. It is also tied to the potential demand on the highway connecting these stations at the given time. While the overall price regime and levels of both station types are chosen primarily for intra-type competition, individual and intra-day price regimes take inter-type competition into account, especially and more consistently for price decreases and diesel fuels.[30] That is, AH stations attempt to undercut BAT competitors significantly, whereas BAT stations aim to preserve the price spread imposed by their contracts and sustained by their location.

Moreover, demand is confirmed as a major driver of competition and pricing regimes for fuel stations in accordance with the Edgeworth cycling model. Higher traffic is strictly associated with an increase in the likelihood for price changes of either direction and fuel type, with marginally stronger effects for undercutting and diesel fuels. The latter is in line with the focus of BAT stations on truckers and business travellers who are more likely to require diesel fuels. The former fits the model of Edgeworth cycles, which postulates quicker, but smaller consecutive price decreases as competition intensifies, followed by one large price increase. This relenting move is also observed and related to the dynamic of demand, i.e. BAT undertake it as traffic rapidly declines (in the evening) or during periods of low traffic. AH, meanwhile, conduct their relenting move as traffic initially mounts or as truck traffic declines.

The relationship between the volume of price changes and demand further supports an Edgeworth interpretation: As the likelihood of undercutting (and matching) increases with demand, the volume of each individual reduction becomes smaller. That is, stations engage in an accelerated undercutting and matching process of the Edgeworth cycle. Correspondingly, the size of price increases is negatively related to present traffic flows, but positively to steep increases in traffic. Timing and scope of the relenting phase are dependent on present demand and its trend. This result again underlines the relevance of controlling for demand when analysing fuel pricing and the competitive nature of even BAT stations: As demand rises, so does competition for it - even for

[30] The stronger effects for price decreases are also a more reasonable result considering brand and firm perspectives because it is generally assumed that systematic price increases by larger brands are coordinated centrally, not executed independently by station operators. Hence, the decreases are more likely to be market outcomes.

BAT stations.[31]

This competitive behaviour is also reasonable from the point of view of station operators. Considering the high fixed costs of operating a fuel station and the comparatively low marginal costs of selling these fuels, competing in prices is profitable only if sufficient quantities can be sold. Otherwise, the additional demand attracted from undercutting and attracting competitors' customers does not offset the lower profits per liter. Then, it is more attractive for the operator to maintain high prices and sell only to the least price-sensitive customers; as observed by the positive link between traffic and the probability for price changes.

3.7 Conclusion

Gasoline pricing remains a contentius topic between accusations of collusion by customers and governments on one side and assertions of competition by the retailers on the other side. Vertical integration of the retailers and local monopolies at more remote locations support the former interpretation, as do the synchronised relenting phases in the market. Yet, this analysis of *Bundesautobahntankstellen* suggest that even these homogeneous, spatially differentiated stations targetting relatively price-insensitive customers are forced to compete in periods of higher potential demand.

This competitive relationship is found to exist across networks - from BAT highway stations to AH road network ones -, but decreases in strength with that transition. It is also lessened by the higher distances between stations and highly related to the competitive pressure originating from rising potential demand. Strategically, the observed competition fits an Edgeworth cycle pattern with its timing aligned to demand and changes therein. Price changes become more likely as demand increases, with more pronounced effects for price decreases. At the same time, the size of individual price reductions decreases, while increasing for the rare price increases denoting the end of a cycle. These are largest and most likely in periods of strong demand shifts. Thus, it is observed that higher potential demand leads to stronger price competition because of the higher undercutting incentives provided by the larger consumer mass.

In terms of policy, this paper comes to the reassuring conclusion that even BAT stations cannot completely isolate themselves from competitive pressure. Their relationship with *Autohof* stations, which are their closest possible competitors, also implies a pro-competitive effect of market entries. While these entries cannot be observed in the study, the presence of AH stations appears to intensify cycling and thereby competition. On a more specific note, this analysis also cautions against the Bundeskartellamt's (2011) view of BAT stations as completely separate from the regular retail gasoline market. While their connection is weak, it exists nonetheless and could perhaps be intensified to the benefit of BAT customers. The construction of more AH stations to enhance competitive pressure or an alteration of the contracts between BAT operators and *Tank & Rast* to reduce the price spread could be means towards this end.

Lastly, this analysis does not provide a causal link and cannot exactly identify price

[31] It should be noted that demand is likely being underestimated in this analysis as it would also impact the pricing decisions of a given station's competitors. This interdependency might not be fully captured by the model.

leaders and followers due to the restrictions of the demand data. Improving upon these points would be a natural venue for future research. The observation of AH entries into the market or an analysis of network intersections (e.g. an unfinished *Autobahn* leading into into another type of road) would also be interesting expansions.

Appendix B

Table 3.6: Average Prices and Competitive Position per Station Type

Prices:

	Competitors			P_{Type}		$N(\Delta P)$	
Type	AH	BAT	Count	E5	Diesel	E5	Diesel
BAT	No	No	1	1.52	1.35	1.29	1.29
BAT	Yes	No	1	1.5	1.36	1.17	1.17
AH	No	No	1	1.5	1.34	1.35	1.35
AH	Yes	No	3	1.49	1.33	1.52	1.52

Location:

	Competitors			No. of Competitors		Avg. Distance to:		Avg. Time to:	
Type	AH	BAT	Count	AH	BAT	AH	BAT	AH	BAT
BAT	No	No	1	0	0	-	-	-	-
BAT	Yes	No	1	1	0	57.15	-	46.66	-
AH	No	No	1	0	0	-	-	-	-
AH	Yes	No	3	2.67	0	37.59	-	21.5	-

Notes: This table provides summary statistics for those BAT and AH stations which cannot be used in the main analysis due to them lacking BAT competitors. The first table displays the yearly average of the hourly station prices and the hourly price changes of that station. The second table displays the competitive situation of that station by listing the number of competitors per type, the average distance to these competitors and the average driving time required to reach them.

Table 3.7: Static Analysis of BAT & AH Station Price Determinants: Sunday, 03:00 - 04:00 AM

	Endog. Var	Price in Level					
	Fuel Type	E5 gasoline			Diesel		
	Station Type	AH	BAT		AH	BAT	
	Comp. Types	AH, BAT	BAT	BAT, AH	AH, BAT	BAT	BAT, AH
	(Intercept)	5.50·	91.37***	75.60***	2.67	56.08**	58.34***
		(2.92)	(25.68)	(12.39)	(2.29)	(18.77)	(10.39)
Wholesale	FOB_E5	0.06	1.17**	1.00·			
		(0.12)	(0.38)	(0.57)			
	FOB_Diesel				0.21	2.41**	1.65*
					(0.16)	(0.88)	(0.80)
BAT Comp.	$\overline{P_{BAT}^{E5}}$	3.44	39.60*	23.16*			
		(2.47)	(17.61)	(10.13)			
	$\overline{N(P_{BAT}^{E5})}$	−4.56*	−1.84**	−0.87			
		(2.18)	(0.71)	(0.76)			
	$\overline{P_{BAT}^{Diesel}}$				3.07	52.57**	23.58*
					(2.12)	(16.91)	(9.47)
	$\overline{N(P_{BAT}^{Diesel})}$				−4.66*	−1.21·	−0.89
					(2.18)	(0.71)	(0.77)
AH Comp.	$\overline{P_{AH}^{E5}}$	93.58***		28.12***			
		(1.67)		(4.52)			
	$\overline{N(P_{AH}^{E5})}$	3.94·		0.69			
		(2.22)		(0.71)			
	$\overline{P_{AH}^{Diesel}}$				94.27***		33.64***
					(1.64)		(6.68)
	$\overline{N(P_{AH}^{Diesel})}$				4.24·		0.04
					(2.26)		(0.70)
Location	Time to BAT	0.01	0.08	−0.03	0.01	0.06	−0.01
		(0.03)	(0.07)	(0.08)	(0.04)	(0.08)	(0.08)
	Time to AH	0.01		0.10·	0.03		0.08
		(0.02)		(0.05)	(0.02)		(0.06)
	No. of Comp.	−0.02	0.06	0.14	−0.00	0.06	0.13
		(0.05)	(0.08)	(0.15)	(0.05)	(0.10)	(0.16)
Brand	Other	−4.42***	−8.23**	−3.40*	−4.47***	−9.59***	−3.89*
		(1.06)	(2.73)	(1.72)	(1.21)	(2.76)	(1.71)
	ESSO	−1.36·	−3.45*	−1.83·	−1.23·	−4.02*	−2.45*
		(0.72)	(1.62)	(0.96)	(0.73)	(1.59)	(1.18)
	Shell	−1.88**	−1.86*	−2.47***	−2.15***	−0.64	−1.24
		(0.58)	(0.78)	(0.66)	(0.56)	(0.95)	(0.83)
	TOTAL	−1.88**	−3.69*	−3.89**	−2.00**	−5.07**	−5.02**
		(0.69)	(1.67)	(1.35)	(0.76)	(1.89)	(1.61)
	Adj. R^2	0.86	0.39	0.14	0.89	0.53	0.22
	Num. obs.	4291	4124	10202	4291	4124	10202

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

Static Analysis for the prices of AH and BAT stations at all Sundays of 2018 for the period from 03:00 to 04:00 AM, in the latter case subdivided into those without and with AH competitors. Stations without BAT or AH competitors are excluded. The first three columns depict results for gasoline, the latter three for diesel. Average Competitor prices are provided in Euro per liter, wholesale prices as 100$/$t$. The number of average price changes by the competitors within that hour is also included. Average time to BAT or AH competitors is the average travel time to the local competitors. Regarding the brand dummies, Aral serves as the base category because its stations have, on average, the highest prices and because it is the largest operator alongside Shell. Outside of these two, Esso and Total also have their own categories, as they are major players in the market. All other owners of BAT and AH stations are subsumed under the *Other* label. Standard errors are clustered on the station level.

Table 3.8: Static Analysis of BAT & AH Station Price Determinants: Wednessday, 17:00 - 18:00

	Endog. Var	Price in Level					
	Fuel Type	E5 gasoline			Diesel		
	Station Type	AH	BAT		AH	BAT	
	Comp. Types	AH, BAT	BAT	BAT, AH	AH, BAT	BAT	BAT, AH
Wholesale	(Intercept)	2.31	76.65^{**}	34.66^{***}	1.23	36.62^{**}	26.01^{***}
		(1.89)	(23.37)	(8.55)	(1.64)	(13.40)	(7.84)
	FOB_E5	-0.01	1.02^{**}	1.09^{*}			
		(0.10)	(0.39)	(0.55)			
	FOB_Diesel				-0.00	2.90^{*}	2.06^{**}
					(0.13)	(1.23)	(0.77)
BAT Comp.	$\overline{P_{BAT}^{E5}}$	4.42^{*}	46.86^{**}	36.61^{***}			
		(1.82)	(16.93)	(9.27)			
	$\overline{N(P_{BAT}^{E5})}$	-0.07	-1.25	0.72			
		(0.30)	(0.93)	(0.57)			
	$\overline{P_{BAT}^{Diesel}}$				4.31^{**}	60.76^{***}	37.86^{***}
					(1.52)	(15.60)	(8.70)
	$\overline{N(P_{BAT}^{Diesel})}$				-0.07	-1.07	0.75
					(0.32)	(0.85)	(0.64)
AH Comp.	$\overline{P_{AH}^{E5}}$	94.43^{***}		39.06^{***}			
		(1.61)		(6.92)			
	$\overline{N(P_{AH}^{E5})}$	0.03		-0.38			
		(0.14)		(0.44)			
	$\overline{P_{AH}^{Diesel}}$				94.98^{***}		37.86^{***}
					(1.61)		(8.26)
	$\overline{N(P_{AH}^{Diesel})}$				-0.03		-0.38
					(0.13)		(0.48)
Location	Time to BAT	0.01	0.11	-0.07	0.02	0.12	-0.07
		(0.03)	(0.08)	(0.08)	(0.03)	(0.09)	(0.08)
	Time to AH	0.01		0.07	0.02		0.05
		(0.02)		(0.05)	(0.03)		(0.05)
	No. of Comp.	-0.01	0.04	0.23	-0.00	-0.01	$0.27^{\cdot}$
		(0.06)	(0.10)	(0.14)	(0.07)	(0.11)	(0.15)
Brand	Other	-2.82^{**}	$-4.54^{\cdot}$	-1.92	-2.95^{**}	-5.01^{*}	-2.38
		(0.97)	(2.52)	(1.59)	(1.08)	(2.54)	(1.63)
	ESSO	-2.91^{***}	-3.04^{*}	-0.79	-2.88^{***}	-4.24^{**}	-1.69
		(0.55)	(1.53)	(0.94)	(0.58)	(1.50)	(1.11)
	Shell	-0.47	1.32	0.85	-0.71	3.33^{**}	2.33^{**}
		(0.47)	(1.03)	(0.69)	(0.46)	(1.20)	(0.89)
	TOTAL	-2.47^{***}	-3.52^{*}	-4.95^{***}	-2.59^{***}	-4.94^{*}	-6.60^{***}
		(0.61)	(1.77)	(1.25)	(0.66)	(1.93)	(1.42)
	Adj. R^2	0.90	0.35	0.27	0.93	0.61	0.37
	Num. obs.	4278	4122	10178	4278	4122	10178

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

Static Analysis for the prices of AH and BAT stations at all Wednesdays of 2018 for the period from 17:00 to 18:00 o'clock, in the latter case subdivided into those without and with AH competitors. Stations without BAT or AH competitors are excluded. The first three columns depict results for gasoline, the latter three for diesel. Average Competitor prices are provided in Euro per liter, wholesale prices as $100\$/t$. The number of average price changes by the competitors within that hour is also included. Average time to BAT or AH competitors is the average travel time to the local competitors. Regarding the brand dummies, Aral serves as the base category because its stations have, on average, the highest prices and because it is the largest operator alongside Shell. Outside of these two, Esso and Total also have their own categories, as they are major players in the market. All other owners of BAT and AH stations are subsumed under the *Other* label. Standard errors are clustered on the station level.

Table 3.9: Determinants of Price Change Decisions: Wholesale & Dummy Details

	Endog. Var	$Prob(P^F > 0)$		$Prob(P^F < 0)$	
	Fuel Type	E5 Gasoline	Diesel	E5 Gasoline	Diesel
Wholesale	ΔFOB_E5	$0.0001^{\cdot}$		-0.000	
		(0.000)		(0.000)	
	ΔFOB_Diesel		0.0002^{**}		-0.000
			(0.000)		(0.000)
Vacation	Start Summer	-0.012^{***}	-0.010^{**}	-0.014^{***}	-0.007^{*}
		(0.003)	(0.003)	(0.003)	(0.004)
	End Summer	-0.026^{***}	-0.021^{***}	-0.035^{***}	-0.022^{***}
		(0.003)	(0.003)	(0.004)	(0.003)
Holiday	State	-0.009^{*}	-0.010^{*}	0.003	-0.000
		(0.004)	(0.004)	(0.004)	(0.004)
	National	0.008^{*}	0.012^{***}	0.031^{***}	0.030^{***}
		(0.003)	(0.003)	(0.004)	(0.004)
Weekend	Sunday	-0.001	0.002	0.014^{***}	0.013^{***}
		(0.003)	(0.003)	(0.003)	(0.003)
	Saturday	$-0.004^{\cdot}$	-0.001	0.008^{***}	0.009^{***}
		(0.002)	(0.002)	(0.002)	(0.002)

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

This table shows the parameters for wholesale prices, vacation, holiday and weekend dummies as used in the main regression of subsection 3.6.2 and displayed in Table 3.4. Wholesale prices are (weakly) significant for price increases only and have small coefficients. This implies a low relevance for intra-day pricing decisions, which is understandable as station operators will insure themselves against volatility and because wholesale prices are posted daily, not hourly. It can be observed that both the start and the end of the state-specific summer vacations leads to a reduced probability of price changes. While the same applies to official state holidays, the opposite can be observed for national holidays which raise the probabilities for price changes in both directions and of both fuel types. Weekends increase the likelihood of price decreases for both fuel types, but barely effect the likelihood of price increases. Given the overall results of higher traffic prompting more intense cycles, national holidays could be considered predictable events of higher traffic, inducing a change in regime towards more fluctuation. Contrastingly, the start and end of state summer vacations would likewise indicate higher traffic volumes, but also presents a shift towards more time-sensitive consumers racing to reach their destinations, thus permitting higher price premiums and less cycling.
Overall, the vacation, holiday and weekend effects have only small impacts.

Table 3.10: Determinants of AH Price Change Decisions

	Endog. Var	$Prob(P^F > 0)$		$Prob(P^F < 0)$	
	Fuel Type	E5 Gasoline	Diesel	E5 Gasoline	Diesel
Demand	Pkw	0.003^{***}	0.003^{***}	0.008^{***}	0.008^{***}
		(0.000)	(0.001)	(0.000)	(0.000)
	Lkw	0.007^{***}	0.006^{***}	0.010^{***}	0.010^{***}
		(0.002)	(0.002)	(0.002)	(0.002)
	ΔPkw	0.055^{***}	0.055^{***}	-0.064^{***}	-0.070^{***}
		(0.009)	(0.009)	(0.009)	(0.010)
	ΔLkw	-0.047^{***}	-0.043^{***}	-0.033^{***}	-0.036^{***}
		(0.011)	(0.011)	(0.007)	(0.007)
Wholesale	ΔFOB_E5	-0.000		0.000	
		(0.000)		(0.000)	
	ΔFOB_Diesel		0.0002^{*}		-0.000
			(0.000)		(0.000)
BAT Comp.	$\overline{\Delta P^{E5}_{BAT}}$	-0.007^{***}		0.014^{***}	
		(0.001)		(0.001)	
	$\Delta P^{E5}_{BAT} > 0$	0.144^{***}			
		(0.010)			
	$\Delta P^{E5}_{BAT} < 0$			0.161^{***}	
				(0.009)	
	$\overline{\Delta P^{Diesel}_{BAT}}$		-0.007^{***}		0.014^{***}
			(0.001)		(0.002)
	$\Delta P^{Diesel}_{BAT} > 0$		0.145^{***}		
			(0.009)		
	$\Delta P^{Diesel}_{BAT} < 0$				0.165^{***}
					(0.009)
AH Comp.	$\overline{\Delta P^{E5}_{AH}}$	0.031^{***}		-0.037^{***}	
		(0.002)		(0.001)	
	$\Delta P^{E5}_{AH} > 0$	0.466^{***}			
		(0.015)			
	$\Delta P^{E5}_{AH} < 0$			0.348^{***}	
				(0.010)	
	$\overline{\Delta P^{Diesel}_{AH}}$		0.029^{***}		-0.035^{***}
			(0.002)		(0.001)
	$\Delta P^{Diesel}_{AH} > 0$		0.467^{***}		
			(0.015)		
	$\Delta P^{Diesel}_{AH} < 0$				0.343^{***}
					(0.010)
Vacation	Start Summer	-0.004	-0.002	0.002	0.001
		(0.004)	(0.004)	(0.005)	(0.006)
	End Summer	-0.003	-0.004	-0.007	-0.004
		(0.003)	(0.004)	(0.005)	(0.004)
Holiday	State	0.009^{*}	$0.009^{\cdot}$	0.018^{**}	0.022^{***}
		(0.005)	(0.005)	(0.006)	(0.006)
	National	0.015^{**}	0.012^{*}	0.012^{*}	0.013^{*}
		(0.005)	(0.005)	(0.006)	(0.006)
Weekend	Sunday	0.013^{**}	0.014^{**}	0.012^{*}	0.012^{*}
		(0.004)	(0.005)	(0.005)	(0.005)
	Saturday	0.007^{*}	0.008^{*}	$0.006^{\cdot}$	$0.006^{\cdot}$
		(0.003)	(0.003)	(0.004)	(0.003)
	Station-FE	yes	yes	yes	yes
	Adj. R^2	0.49	0.49	0.44	0.43
	Num. obs.	719,747	719,747	719,747	719,747

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

Analysis of the determinants of hourly price change decisions for all AH stations in 2018. Standard errors are corrected for autocorrelation and heteroskedasticity using Arellano's method with clustering on the station level. Hence, the R^2 is not informative. Columns (1) and (2) depict the determinants of the decision to raise prices for a given station in a given hour for gasoline and diesel, respectively. Columns (3) and (4) depict the same for the decision to lower prices. The control variables include hourly truck and car traffic, in 100 vehicle steps, as well as its trend. First differences of distance-weighted competitor prices and dummy variables indicating their pricing decisions are included for each fuel and station type. Information on AH competitors must be understood as an interaction term of the variable itself and the existence of AH competitors. Holidays, the start and end of summer vacations and weekends are demarked by dummies. Fixed effects and wholesale prices in first differences are included.

Table 3.11: Determinants of the Absolute Volume of Price Change Decisions: Dummy Details

	Endog. Var	$\lvert\Delta p_{it}\rvert$			
	Fuel Type	E5 Gasoline		Diesel	
	, if:	$\Delta p_{it} > 0$	$\Delta p_{it} < 0$	$\Delta p_{it} > 0$	$\Delta p_{it} < 0$
Vacation	Start Summer	-0.34^{***}	-0.36^{***}	-0.09	-0.17^{**}
		(0.05)	(0.05)	(0.06)	(0.05)
	End Summer	-0.34^{**}	-0.24^{*}	-0.26^{***}	-0.26^{***}
		(0.12)	(0.11)	(0.06)	(0.05)
Holiday	State	-0.40^{***}	-0.44^{***}	-0.41^{***}	-0.45^{***}
		(0.07)	(0.06)	(0.09)	(0.07)
	National	0.00	-0.03	-0.13^{*}	-0.15^{*}
		(0.05)	(0.06)	(0.06)	(0.06)
Weekend	Sunday	-0.12^{**}	-0.16^{***}	-0.12^{**}	-0.18^{***}
		(0.04)	(0.04)	(0.04)	(0.04)
	Saturday	-0.11^{***}	-0.15^{***}	-0.09^{**}	-0.15^{***}
		(0.03)	(0.03)	(0.03)	(0.03)

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

This table shows the parameters for vacation, holiday and weekend dummies as used in the main regression of subsection 3.6.3 and displayed in Table 3.5.
Both the start and the end of the summer vacation periods have a contracting influence on price changes, i.e. smaller decreases and increases in cent per liter, especially for gasoline by 0.24 to 0.36 cent per liter. Both may reflect strategy changes reacting to holiday travellers in addition to the demand effects caused by their travel. State holidays similarly contract price changes by 0.4 to 0.45 ct/l, whereas national holidays interestingly only affect diesel prices, presumably through strategy changes in reaction to depressed truck traffic. Saturdays and Sundays similarly contract volume changes weakly. In general, these coefficients imply a reduction in price volatility over the tested days and periods, which might result from a more even and less commercial traffic distribution throughout the day. That would lead to fewer peak demand phases and as a result to fewer undercutting operations.

Table 3.12: Determinants of the Absolute Volume of AH Price Change Decisions

	Endog. Var	$\lvert\Delta p_{it}\rvert$			
	Fuel Type	E5 Gasoline		Diesel	
	, if:	$\Delta p_{it} > 0$	$\Delta p_{it} < 0$	$\Delta p_{it} > 0$	$\Delta p_{it} < 0$
Demand	Pkw	-0.02^{***}	-0.03^{***}	-0.02^{***}	-0.03^{***}
		(0.00)	(0.00)	(0.00)	(0.00)
	Lkw	0.00	-0.04^{**}	0.02	-0.03^{**}
		(0.01)	(0.01)	(0.01)	(0.01)
	ΔPkw	0.31^{**}	0.06	0.40^{***}	0.12^{**}
		(0.10)	(0.04)	(0.11)	(0.04)
	ΔLkw	0.11	0.10^{*}	0.04	0.09^{*}
		(0.07)	(0.04)	(0.09)	(0.04)
BAT Comp.	$\overline{\Delta P^{E5}_{BAT}}$	0.05^{***}	-0.08^{***}		
		(0.01)	(0.01)		
	$N(\Delta P^{E5}_{BAT} \neq 0))$	0.13	$0.10^{\cdot}$		
		(0.10)	(0.05)		
	$\overline{\Delta P^{Diesel}_{BAT}}$			0.04^{**}	-0.08^{***}
				(0.01)	(0.01)
	$N(\Delta P^{Diesel}_{BAT} \neq 0))$			0.16	$0.11^{\cdot}$
				(0.13)	(0.06)
AH Comp.	$\overline{\Delta P^{E5}_{AH}}$	0.50^{***}	-0.42^{***}		
		(0.02)	(0.02)		
	$\lvert\overline{\Delta P^{E5}_{AH}}\rvert \upuparrows$	0.46^{***}	0.83^{***}		
		(0.07)	(0.07)		
	$N(\Delta P^{E5}_{AH} \neq 0))$	0.16^{**}	-0.14^{***}		
		(0.06)	(0.03)		
	$\overline{\Delta P^{Diesel}_{AH}}$			0.55^{***}	-0.45^{***}
				(0.02)	(0.02)
	$\lvert\overline{\Delta P^{Diesel}_{AH}}\rvert \upuparrows$			0.43^{***}	0.86^{***}
				(0.07)	(0.08)
	$N(\Delta P^{Diesel}_{AH} \neq 0))$			$0.10^{\cdot}$	-0.15^{***}
				(0.06)	(0.04)
Vacation	Start Summer	0.01	0.02	0.08^{*}	0.11^{**}
		(0.04)	(0.03)	(0.04)	(0.03)
	End Summer	0.01	-0.01	0.03	0.01
		(0.04)	(0.03)	(0.04)	(0.03)
Holiday	State	$0.12^{\cdot}$	0.06	0.16^{**}	0.06
		(0.06)	(0.05)	(0.06)	(0.05)
	National	-0.04	-0.10^{**}	0.06	$-0.07^{\cdot}$
		(0.05)	(0.04)	(0.06)	(0.04)
Weekend	Sunday	0.06	-0.03	0.11^{*}	-0.01
		(0.05)	(0.03)	(0.05)	(0.04)
	Saturday	0.05	$-0.05^{\cdot}$	0.09^{*}	-0.03
		(0.03)	(0.03)	(0.03)	(0.03)
	Adj. R^2	0.38	0.28	0.43	0.32
	Num. obs.	$214,067$	$278,704$	$214,743$	$278,992$
	Station-FE	YES	YES	YES	YES

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

Analysis of the determinants of the volume of all price change decisions in 2018 for all AH stations. Standard errors are corrected for autocorrelation and heteroskedasticity using Arellano's method with clustering on the station level, hence the R^2 is not informative. The dependent variables are the absolute cent/liter changes in E5 gasoline and diesel prices for positive - columns (1) and (3) - and negative changes - columns (2) and (4). respectively. Gasoline is shown first, diesel second. Demand variables are the hourly truck and car traffic, in 100 vehicle steps, as well as their trends. Competitor behaviour is assessed by the first differences of distance-weighted competitor prices and the number of price changes in the given hour by BAT and AH stations. Information on AH competitors must be understood as an interaction term of the data itself and the existence of AH competitors. Holidays, the start and end of summer vacations and weekends are demarked by dummies and fixed effects are included.

Acknowledgments

I am grateful to Michael Noel, Nicolas De Roos, Klaus Gugler, Justus Haucap and colleagues at DICE for helpful comments and suggestions,

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Chapter 4

Economic Preferences and Trade Outcomes

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4.1 Introduction

International trade, while currently beleaguered by protectionism and trade wars, is established in economics as an engine of growth, welfare and progress. Its potential for division of labour, specialisation and efficient use of capital is unmatched by any domestic policy, which would inevitably be faced with rigidities and restrictions in these factors. Nonetheless, the intensity of international trade has been stagnant below assumed efficient levels even before the protectionist trends of the present. The causes for these so-called "dark" trade costs remain unknown, preventing both a solution and a more optimal outcome.

In response to these anomalies. trade literature has expanded the concept of economic gravity, based on market size, output and distances, by non-tariff barriers like cultural factors. These persistent differences, ranging from language or colonial history to shared values and even genetic distance, however, do not provide a mechanism by which these characteristics would impact trade outcomes. Instead, they are often treated akin to physical distance, a natural barrier needing to be overcome for trade interaction to emerge.

This paper explores a possible mechanism linking culture with trade outcomes by introducing term (patience) and risk preferences as well as reciprocal behaviour into a trade context using, for the first time, the GPS preference data by Falk *et al.* (2018). These preferences, likely shaped by culture and society within a given country, might affect negotiations between firms and agents of different nations. They inform their time horizons, influencing discounted values of a deal, their willingness to risk investment into a trade relationship and their responses to (non-)cooperative behaviour. Each of these four aspects could help explain trade outcomes and anomalies in volume between economically similar country pairs. The GPS is particularly well-suited to this analysis because of its broad scope and quality, covering 76 countries through nationally representative surveys on these preferences and experimental validations for them.

Analytically, this paper is the first, to the best of the authors' knowledge, to join the gravity model for trade with specific data on population preferences directly relating to economic decisions, specifically contract motivation and incompleteness. It thus expands the gravity model by a new dimension of non-tariff barriers and provides a possible explanation for the effect of cultural distances on trade outcomes as well as towards explaining "missing trade" and "dark trade costs".

Preferences are integrated into the gravity framework using a two-step approach: Distances in preference are incorporated into a standard gravity model to measure the effects of differences in reciprocity as well as term and risk transformation considerations. The preference levels, meanwhile, are analysed by decomposing the multilateral resistance terms of the gravity equation, a country's overall propensity towards trade, thus discerning potential shifts in trade inclination associated with specific preference leanings.

This approach yields that distances in reciprocity and term and risk orientation levels affect trade outcomes. Specifically, a distance in negative reciprocity, i.e. the willingness to engage in costly punishment, is detrimental to export volumes by introducing unexpected costs in case of transaction issues. Conversely, distances in positive reciprocity, i.e. rewards for cooperation, intensify existing trade relationships. Long-term orientation and higher risk aversion, meanwhile, lower the average trade barriers for differentiated goods, while raising them for non-differentiated ones; less risk aversion and shorter term orientation have the opposite effects. This reflects term and risk transformation by national players, wherein a product mix is selected whose trade and contract conditions reflect term and risk profiles. That is, the longer the term orientation the more complex and differentiated the product mix, and: the more risk-tolerant the more volatile and non-differentiated the produced goods. Lastly, preference effects are overall stronger for differentiated goods and OECD-countries, indicating the link between preferences and negotiation intensity.

The rest of the paper is structured as follows. The paper is related to the existing literature in section 4.2, followed by a summary of the hypotheses for the analysis in section 4.3. The data and empirical strategy are introduced in section 4.4, whose results are reported in section 4.5. A set of robustness checks is discussed in section 4.6, before the paper concludes in section 4.7 with a short discussion on the results and considerations for further research.

4.2 Related Literature

This paper aims to link two fields of economic literature: the analysis of trade flows, especially non-material barriers to trade, and the literature on behavioural economics. Contract theory is utilised as the mechanism for this conjunction.

In regard to the trade literature, we contribute to the shift in discussion from conventional drivers like size and transportation costs to "missing trade" (Trefler, 1995) and "dark" trade costs (Head and Mayer, 2014) by proposing a novel influence in the form of national preference leanings and a simple mechanism by which its influence would occur. We follow previous analysis on cultural differences such as Melitz and Toubal (2014), who analysed the effects of a shared language and revealed a channel of shared ethnicity in the process, and Lameli *et al.* (2015), who discovered a trade-boosting effect between German regions sharing similar dialects. Similarly, Felbermayr and Toubal (2010) have investigated a proxy for cultural proximity as a determinant of trade flows and Fensore *et al.* (2017) have introduced genetic distance as a measure to this end as well.[1]

Bilateral trust has also been extensively studied in the trade context, for example by Guiso *et al.* (2009) or Yu *et al.* (2015), who find positive effects of trust on trade activity. Unfortunately, the trust measures of the GPS are too broad to allow comparison. Closest to our analysis are Frank (2018) and Jaeggi *et al.* (2018) who analyse cultural attitudes - future orientation and other from the GLOBE survey in the former, and a dyadic values distance measure computed using the World Values Survey in the latter - as factors for overall economic development. Genetic and values distance are consequently used as robustness checks in this analysis. However, we differ from their approaches in two ways: by also considering potential positive effects of such divergence and by proposing a channel for these effects to occur in by introducing behavioural concepts and contract theory.

With regard to that connection, our analysis is related to the GPS itself (Falk

[1] The latter's results have been challenged by Giuliano *et al.* (2013), however.

et al., 2018, 2016) and research by Dohmen *et al.* (2016) linking patience with national economic development. However, we also relate to a broader lecture linking the preferences also measured in the GPS to individual outcomes. This includes Sutter *et al.* (2013) who links time and risk preferences to saving and smoking decisions, Kihlstrom and Laffont (1979) who investigate entrepreneurial activity with regards to the risk preferences of the players, and Fehr and Gächter (2000, 2002), Fehr *et al.* (1997) and Nikiforakis (2008) who all investigate the effects of reciprocity preferences on collective action and their outcomes. Here, we contribute to the literature by observing expressions of these individual decisions and outcomes on the aggregate level.

Relatedly, these individual considerations have also been considered in trade finance and contract theory. Trade finance specifically deals with the management of risk in a trade context, which is typically placed primarily on the exporter (Ahn, 2011, Antras, 2003) - a finding we also observe. Given these risks and uncertainties, it is unsurprising that complex, but incomplete contracts govern the actual trade interactions. In addressing these complex contracts and their dynamic nature, Defever *et al.* (2016) and Kukharskyy (2016) also showed that only sufficiently patient firms may establish efficient supplier collaborations. Findings by Aeberhardt *et al.* (2014), Araujo *et al.* (2016) and Rauch and Watson (2003) point to relationships being established slowly, starting with small test orders until a relationship is established. We build upon both of these relationships in this analysis by attempting to investigate their more abstract, global effects using the GPS.

4.3 Hypotheses

In this section, the hypothetical mechanisms by which preferences might affect trade outcomes are presented and their directions summarised. For each of the four GPS dimensions patience, risk, positive and negative reciprocity, two effects are considered: level and differences. That is, a preference could matter unilaterally and shift a country's general attitude towards trade or it could matter only in contrast to the partner's preference distributions. The resulting eight dimensions are displayed in Table 4.1.

For a simple guiding structure, consider a Home firm looking for a supplier.[2] Its outside option is to immediately buy from a local supplier H with guaranteed quality and quantity x_H, thus allowing a safe final payout y_H and profit π_H:

$$\pi_H = y_H - c_H x_H \tag{4.1}$$

International profits, by contrast, take the following form:

$$\pi_T = -c_T x_T + \delta[p y_T + (1-p) d y_T] \tag{4.2}$$

Therein, it is is assumed that international partners promise a higher payout, be it through lower buying prices, i.e. $c_T < c_H$, better quality or access to a unique variety of a good or input, i.e. $x_T > x_H$, but also $y_T > y_H$, but also a delayed realization (valued at discount factor δ) and the risk of default with probability $(1-p)$. The ordered goods

[2] Analogously, the same channels can be transformed to different settings, e.g. a Home producer looking to export to a Foreign distributor, or to the viewpoint of the Foreign firm.

may never arrive, or, vice versa, the firm may default on the payment. One may extend this setting with the possibility of a partial payout of share d, applying to situations of deliveries of insufficient quantity or quality, but also to a potential enforcement and recoupment with some probability.

Within this structure, players formulate expectations for the discount factor, default and recoupment probabilities, upon which they would calculate expected values for a given trade relationship. These calculations and thus the outcomes might be shaped or influenced by the preference leanings of the players involved. In the following, the rationale for each of the four dimensions investigated in this analysis is provided.

Table 4.1: Summary of the Hypotheses for Preferences

	Effect on Trade Volumes	
Dimension	Preference Level	Distance in Preference
Patience	+	+/0
Risktaking	+/-	+
Pos. Recip.	0	+
Neg. Recip	+/-	-
Overall		-

Notes: This table summarizes the hypothesized effect of the four preference dimensions patience, risk attitude, positive and negative reciprocity on trade outcomes as well as for the average bilateral distance over all dimensions. It provides hypotheses for both the unilateral level of a preference dimensions and the bilateral distance between two countries in that dimension.
+ implies a positive relationship, - implies a negative one, *+/-* an unclear relationship and *+/0* one that could be positive or non-significant. An empty entry signals that no effect can exist.

Patience Patience measures the willingness to forego short-term profits for higher gains in the long-run and is equivalent - or at least related - to the discount factor δ in the contract setting above. Higher levels of patience should imply a lower discount factor and thus be beneficial for trade volumes and intensity, as the expected value of trade would rise. This builds on the understanding of trade as a means to achieve efficiency gains by constructing international supply and distribution networks, allowing greater specialization. Since the construction of these networks, from contract negotiations to physical construction and transport times, requires time and effort, more patient agents would be more likely to engage in these activities than impatient agents, which would conversely be more likely to engage with local partners despite the long-term disadvantage.

Given this hypothesis, the effect of distances in patience is unclear ex ante. Differently patient players could benefit from term transformation. That is, they could specialize their production mixes in accordance with their time horizons, thus achieving a kind of efficiency gain not accessible to partners with similar outlooks. However, this efficiency gain need not be a trade volume expansion, but could also constitute a shift in exports through such specialization. In the latter case, an effect would only exist in trade structure, not in volume.

Risk-aversion In general, less risk-aversion should facilitate the buildup of trade relations because of the specific trade-inherent risks mentioned above which would appear more bearably to more risk-taking individuals. In the contract context of this analysis, the expected default probability $E[](1-p)]$ would be reduced. However, considering the greater picture of trade, it might be risk-minimising to diversify into a multitude of international relationships, lowering the exposure to local shocks. Note that this diversification argument applies to both securing access to inputs and to maintaining steady sales and cashflows. Hence, the effect of risk-taking levels on trade outcomes is unclear ex ante.

On the other hand, the effect for bilateral distances in risk attitude should be positive. A divergence in risk perceptions should allow for risk transformation, similar to the term transformation for patience, with regards to the product mix of the players of a given country pair.

Positive reciprocity In general, the presence of a more positively reciprocal player should stabilize commercial agreements by inducing cooperation. This can be achieved through positive feedback loops caused by reliable and timely deliveries and payments, which would build up goodwill on both sides of the relationship.[3] In the framework of this analysis, positive reciprocity would - again - lower the perceived risk of default $E[(1-p)]$. Alternatively, positive reciprocity could assume the shape of rebates or more accomodating terms of payment within an active and ongoing relationship, thus lowering costs and building trust.

Consequently, the distance in positive reciprocity should have a positive effect due to the implied presence of one highly positively reciprocal partner. In such a relationship, the reciprocal behaviour of that partner would be viewed akin to a standard gift exchange (cf. Akerlof, 1982) and thus strengthen the relationship between the players. Such an unexpected and beneficial effect cannot emerge between two highly reciprocal partners, who would each expect it, and two lowly reciprocal partners, who would not commit it. Moreover, the effect of positive reciprocity can only manifest within existing relationships. Hence, it would neither shift the overall approach to trade nor the extensive margin.

Negative reciprocity Lastly, the effect of negative reciprocity is more complicated. On one hand, higher levels imply a willingness to punish deviation from contracts and agreements - even beyond a level where it would be monetarily rational to do so -, thus raising the cost of a breach of contract once it has been established. While this might partially deter some initial agreements in the first place, the prospect of a more credible punishment could help to prevent deviation and therefore foster the establishment of

[3]Corresponding results or interpretation are common in the literature. Fehr *et al.* (1997) have stresed the importance of reciprocity in non-enforceable contracts especially, while Gächter and Herrmann (2009) showed that positive reciprocity may induce selfish types to cooperate and Cable and Shane (1997) proposes positively reciprocal cooperation as a key aspect in an entrepreneur's efforts to acquire capital and develop alliances with larger companies.

persistent trade relationships. For example, Dohmen *et al.* (2008) highlight this ability to make credible threats as a potential bargaining advantage.

However, this seems to only hold true for milder forms of negative reciprocity. In its strongest forms - decisively taking revenge and anti-social punishment -, negative reciprocity may actually hinder coordination and cooperation (Gächter and Herrmann, 2009, Herrmann *et al.*, 2008). In the contract framework applied here, the risks associated with the threat of punishment could raise the expected risk of default and the costs via reserves for contingencies. Caliendo *et al.* (2012) also find that a propensity to take revenge has a negative effect on the probability of staying in entrepreneurship, suggesting that high levels of negative reciprocity reflect non-cooperation and reduce one's own profits.

More importantly, if partners differ in negative reciprocity, the actions of the more negatively reciprocal partner might antagonize or alarm the less reciprocal partner. Thus, larger distances in negative reciprocity are expected to reduce bilateral trade. For the level effect, the null assumption defined for positive reciprocity applies also.

Overall Bilateral Distance Following the literature on shared characteristics in trade such as language, ethnicity and culture, the effect of overall preference distances between two countries is also analysed. This serves two purposes. First, it allows a comparison to studies regarding such shared characteristics and to control for a potential correlation with them. Second, it allows testing the hypothesis that partners with more similar preference sets would be more likely to trade with one another solely on account of that greater similarity causing affinity.

4.4 Data & Empirical Strategy

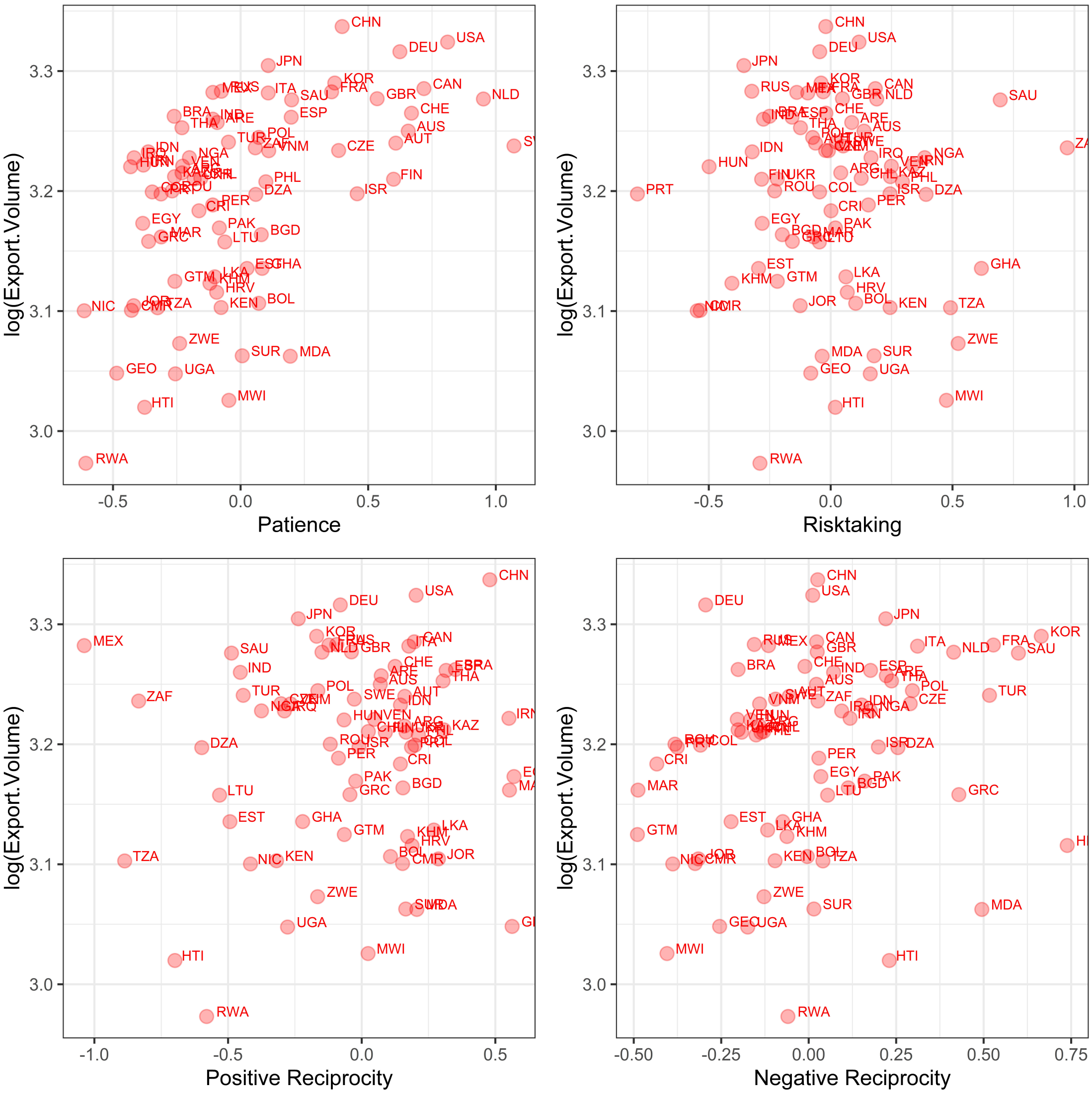
Mapping and isolating the potential impact of preferences on trade requires a comprehensive, three-part data set consisting of the GPS' preference data, the corresponding trade data and a set of cultural and institutional controls. The following subsections will be dedicated to describing the data used and the empirical strategy.

4.4.1 Data

Preference Data The main variables of interest are the GPS' results detailing a six-dimensional preference structure for 76 countries: patience, risktaking, positive and negative reciprocity, trust and altruism. Patience is therein understood as a broader measure of term orientation or time discount considerations, whereas risk assesses the average risk premium of a given population. Positive reciprocity is the willingness to reward cooperative behaviour and, consequently, negative reciprocity the willingness to conduct costly punishment of non-cooperative or deviant behaviour. Altruim is defined as the willingness to contribute to good causes or give to others, while trust is defined - more broadly - as the belief in other people's good intentions. All preferences are considered to be persistent, underlying convictions or notions, related to upbringing, education, norms and other societal trends.

The GPS was conducted alongside the 2012 Gallup World Poll, utilising the infrastructure and scope of that survey to gain both coverage and size. The Gallup World

Figure 4.1: Preference Structure and Trade Volume



Notes: Relationship between the natural logarithm of exports and GPS preference values for all countries in the GPS for which trade volumes can be computed.

Poll interviewed representative samples of at least 1,000 persons per covered country and uses tried weighting techniques for these samples to match a nation's population. The GPS' data covers all important global economies with the possible exception of Africa. Around ninety percent of world population and GDP lie within the sample borders. Africa's coverage is less dense than for the other continents, but both Sub-Saharan and North African countries are included, which permits their use without disregarding the structural differences imposed by the Sahara desert (see Falk *et al.*, 2018). This scope permits conclusions beyond the traditionally available data from more developed countries only. This size and the World Poll's methodology elevate the GPS above previously available measures.

Additionally, the survey items - except for negative reciprocity and trust - are experimentally validated (see Falk *et al.*, 2018), in that incentivized experiments were conducted to evaluate the fit between survey answers and revealed preferences in the experiment. This factor differentiates the GPS from other typically questionnaire-only surveys of similar intent by contextualizing the preferences as economic. The focus is shifted from abstract cultural measures and perceptions to their role in decision-making. Via that channel, these preferences inform negotiations, defining term and risk profiles and behaviour in interaction.

Unfortunately, the definitions for altruism and trust used for the GPS are too general for use in this context. Trust is measured by the participants' level of agreement to the statement *I assume that people have only the best intentions* (see Falk *et al.*, 2018), which does not reflect managerial intent. Even if both sides in a negotiation had the best intentions, they still represent different interests. More importantly, the measure does not consider specific national or bilateral biases, which might overrule a person's general outlook; indeed, previous research into the role of trust for trade specifically investigates such bilateral perceptions of trustworthiness (e.g. see Yu *et al.*, 2015). Altruism, measured by the willingness to donate to good causes[4], likewise does not reflect the situation faced by a negotiator. Hence, both measures are excluded from the main analysis, but assessed in the robustness section.

As for the preferences themselves, they are provided in a normalized distribution, calculated in a three-step procedure. First, individual-level data on the experimental and survey data is combined using weights obtained by OLS regression on behavior observed in the experimental validation study conducted beforehand (see Falk *et al.*, 2016). Secondly, these measures are standardized with regard to the full sample of around 80,000 individuals from all 76 countries. Hence, each preference is, by design, of mean zero and standard deviation one on individual levels. Third - and lastly -, individual-level data of each country is aggregated to the national average using Gallup World Poll sampling weights. As a result, the national averages are representative of a respective country's population and similarly have means close to zero. Their standard deviations lie between 0.27 and .37, with explicit minima and maxima diverging from symmetry (see Table 4.2). Figure 4.1 relates GPS values to national export volumes only, providing an overview of the country's preference distributions.[5]

[4] The willingness is assessed by a question directly inquiring the willingness to donate without expecting a return and by the reply to a hypothetical question on how much one would donate, if given a 1,000 Euro.

[5] Table 4.7 and Figure 4.2 analogously summarise the preference distances and their relationships to trade volumes.

Table 4.2: Descriptive Statistics of the GPS Variables

Statistic	Mean	St. Dev.	Min	Max	Top 3	Bottom 3
Patience	0.001	0.377	−0.613	1.071	SWE, NLD, USA	NIC, RWA, GEO
Risktaking	0.006	0.298	−0.792	0.971	ZAF, SAU, GHA	PRT, NIC, CMR
Pos. Recip.	−0.042	0.344	−1.038	0.570	EGY, GEO, MAR	MEX, TZA, ZAF
Neg. Recip	0.007	0.276	−0.489	0.739	HRV, KOR, SAU	GTM, MAR, CRI

Notes: Each of the preferences is normalized on the individual level, then aggregated to national averages using Gallup World Poll weights. Hence, their means are close to but not exactly zero. Standard deviations range from 0.275 to 0.37, as substantial variation occurs between individuals and within nations. Minima and maxima highlight an asymmetry in preference distributions. For each preference, the three countries with the highest and lowest preference values are provided in order.

Culture, Politics and Institutions Preferences might be correlated with other cultural variables. They could also interact with institutional settings, as has been found for trust and rule of law (Yu *et al.*, 2015), or the overall economic situation. To account for these potential biases, a broad range of cultural, historic, political or economic indicators supplements the preference data. This includes population, GDP and other national characteristics from the CEPII (Head and Mayer, 2014, Head *et al.*, 2010) as well as information on geography and colonial history (Mayer and Zignago, 2011). Additional data on country terrain is drawn from Nunn and Puga (2012), who measure the ruggedness - i.e. differences in altitude - within a country, a potential measure for physical trade barriers[6]. Information on regional trade agreements is extracted from Egger and Larch (2008).

Data on linguistic similarities is integrated using data from Melitz and Toubal (2014), who provide and compare multiple measurements for the resulting ease of communication. In the same vein, information regarding cultural, religious and genetic distance from Spolaore and Wacziarg (2016, 2018) is used to account for the more general effects of alien- or likeness. The Dyadic Values Distance measure created by Jaeggi *et al.* (2018) and drawn from the World Values Survey is included for contrast and comparison; as are the Hofstede dimensions (see Hofstede *et al.*, 2010).

For political and institutional influences, the Polity scores (2018), Freedom House indices (2018), and Worldwide Governance Indicators (Kaufmann *et al.*, 2009) are used. These assess democratic or autocratic leanings and civil liberties as well as issues of politic representation, respectively. Thus, the measures can be used as proxies for legal rights and personal freedom, which might both impact negotiation behavior and outcomes.

Trade Data The trade data used in the analysis is obtained from UN Comtrade for 2012, the year in which the GPS had been conducted, at the 3-digit industry level (SITC, Rev. 4). Flows are measured using import data, which is considered more

[6]However, these measures were excluded from the final results to consolidate variables used in the second stage on account of the low number of observations. Since their exclusion does not alter results significantly, this seemed an acceptable compromise. Nonetheless, their potential influence had to be controlled for.

accurate due to customs and tariff requirements of the receiving country. All 240 goods categories are observed for 68 countries of the GPS. The disaggregated data is used to divide trade flows into listed, reference priced and differentiated goods according to Rauch (1999), as these groups might respond differently.

A subset of ten nations available in the GPS - Afghanistan, Botswana, Cameroon, Haiti, Iran, Iraq, Kenya, Morocco, Philippines and Venezuela -, have not yet reported for 2012. Their flows are calculated using export data from their 66 partner countries[7]. Additionally, Bosnia-Herzegovina and Serbia are dropped due to the risk of confounding with Yugoslavia for several cultural variables, while Afghanistan is dropped due to a general lack in controls.

Given these corrections, the final dataset contains 73 countries from all continents, yielding 5256 exporter-importer pairs and 1,261,440 bilateral good-specific trade flows. Of these, 35.8 percent are non-zero, whereas the average value of a bilateral good-specific trade flow amounts to 8.9 million US-Dollar. The average country trades with 67 out of 72 potential partners and in 86 out of 240 goods categories.[8]

4.4.2 The Model

The analysis is built upon the Gravity framework by Anderson and van Wincoop (2003) and its expansions by Head and Mayer (2014), Yotov *et al.* (2016) and Santos Silva et al. (2006, 2014). Therein, international trade x_{ij}, between exporter $i = 1, ..., I$ and importer $j = 1, ..., J$, is modeled as:

$$x_{ij} = \underbrace{\frac{Y_i}{\Omega_i}}_{S_i} \underbrace{\frac{X_j}{\Phi_j}}_{M_j} \phi_{ij} \tag{4.3}$$

Y_i and X_j are the total values of exporter production and importer expenditure, respectively, and ϕ_{ij} describes the bilateral trade costs between i and j, which are assumed to be symmetric. Ω_i and Φ_j represent the multilateral resistance terms, a representation of the average trade barriers faced by exporters. These terms can be defined as:

$$\Omega_i = \sum_l \frac{\phi_{il} X_l}{\Phi_l} \quad \text{and} \quad \Phi_j = \sum_l \frac{\phi_{lj} Y_l}{\Omega_l} \tag{4.4}$$

Ω_i is the expression of an exporter i's average cost of exporting to any other country, and Φ_j correspondingly the average cost of importing into country j.[9] An alternative designation is that of outward and inward multilateral resistance term, respectively (see Donaubauer *et al.*, 2018). With the Gravity framework's three cost parameters, ϕ_{ij}, Ω_i and Φ_i, the potential effects of GPS preferences can be studied. Differences between them could influence transaction costs by affecting negotiations through aligning term

[7]See section 4.7 for further detail regarding potential bias inherent in the use of reported data from both trade flows. Note also that trade between these countries is missing entirely, causing potentially non-negligible bias.

[8]Note that only 72 countries can be used in the main analysis due to lacking control variables.

[9]More precisely, the average trade barrier of one exporter (importer) is constructed as the sum of bilateral trade costs weighted by the expenditure (consumption) share of each flow and the respective partner's own average import (export) costs. In its pure form, this could only be solved iteratively or given a complete set of trade costs.

and risk transformation objectives or reciprocal gestures. These preference distances thus constitute a bilateral cost parameter (ϕ_{ij}), which also permits comparison with the similarly modelled cultural differences. Preference leanings, meanwhile, could influence the overall openness to trade of a given population by defining its outlook. They can be analysed only akin to unilateral economic variables, i.e. as part of the resistence terms Ω_i and Φ_j.

Intensive Margin Both multilateral resistance terms are typically modelled as fixed effects, S_i and M_j (see Equation 4.3), due to computational and information restrictions. This method also accounts for unobserved heterogeneity in trade determinants. Given the assumption of persistence for preferences, a country's preference leanings would be subsumed under the fixed effects. However, these fixed effects and its components can be analysed in a two-step approach using a Gravity specification first and OLS on the estimated fixed effects (cf. Donaubauer *et al.*, 2018, Head and Mayer, 2014) second, permitting analysis of the preference levels in a trade context. In accordance with the wider literature, that specification is estimated using Pseudo Poisson Maximum Likelihood (PPML), which is both consistent in the presence of heteroskedasticity and allows the inclusion of zero trade flows (Santos Silva and Tenreyro, 2006). The first step estimator is defined as:

$$x_{ij} = exp\left(|\boldsymbol{z_i} - \boldsymbol{z_j}|\,\boldsymbol{\beta} + S_i + M_j + \boldsymbol{\phi'_{ij}}\boldsymbol{\gamma}\right) + \epsilon_{ij}, \tag{4.5}$$

where S_i and M_j are the exporter and importer fixed effects - or average trade barriers, including preference levels - and $\boldsymbol{\phi_{ij}}$ is a vector of bilateral (dyadic) trade cost variables. x_{ij} is the volume of exports from country i to country j, the intensive margin of trade. $|\boldsymbol{z_i} - \boldsymbol{z_j}|$ is a measure for preference distances between a country pair. Each of the four preferences patience, risk, positive and negative reciprocity is included separately. The use of absolute distances serves three purposes. First, it distinguishes the distances from the levels (leanings), allowing effect decomposition. Second, it abstracts from the direction of distances, which might conflate effects otherwise due to its correlation with the levels[10]. Third, it is necessary as the provided GPS variables are normalized, for which reason normal differences cannot be estimated.[11]

The gravity equations are applied to both the total bilateral trade volumes and separate volumes for differentiated and non-differentiated goods. This split accounts for the fact that negotiations, the effect channel, would play a more important role for differentiated goods than for listed or reference-priced commodities. The more goods diverge from a global standard, the more details need to be covered in the bilateral negotiations and the less can be relied on that standard to assure an effective contract and relationship. This split is achieved using the Rauch (1999) classifications for three-digit SITC 4 commodity classes, yielding 240 separate potential bilateral flows per country pair, which are then aggregated into two export volumes for each of the groups.

In the second step, the estimated exporter and importer fixed effects are each

[10] Inclusion of these directions as dummy variables does not alter results, however.

[11] In the robustness section, alternative approaches are tested: the maximum and minimum preference values of each pair, an inclusion of the direction, and the maximum and minimum values if they are more than one standard deviation distant from the mean.

regressed on their respective preference measures $\boldsymbol{z_i}$ and country-specific variables $\boldsymbol{C_i}$ such as GDP per capita, population and internal distance:

$$S_i = \alpha_0 + \alpha_1 \overline{\phi_i} + \boldsymbol{C_i}'\boldsymbol{\delta} + \boldsymbol{z_i}'\boldsymbol{\eta} + v_i \quad and \quad M_i = \alpha_0 + \alpha_1 \overline{\phi_i} + \boldsymbol{C_i}'\boldsymbol{\delta} + \boldsymbol{z_i}'\boldsymbol{\eta} + v_i, \tag{4.6}$$

where $\overline{\phi_i}$ is the weighted average over the dyadic characteristics of each country $\overline{\phi_i} = \sum_j \boldsymbol{\phi'_{ij}}\hat{\boldsymbol{\gamma}}$.[12]

National preference leanings and bilateral differences are thus analysed separately: The parameters in the gravity equation measure only the impact of differences in preferences, a dimensionless discrepancy in outlook, while the fixed effects decomposition informs on the change in the willingness to trade implied by high and low national preference measures, respectively.

Extensive Margin So far, the impact of preferences has been modeled as one of repeated interactions within existing commercial relationships, that is: the intensive margin, the volume of non-zero trade flows. Yet negotiations and other communication also take place during the inception of trade, that is: the change from a zero flow to a non-zero one - the extensive margin. While it is impossible to gain a measure for that exact moment in time when a first contract between firms for a country pair and specific good is formed, an average over these events can be approximated via measures for the number of traded goods categories. This limitation conveniently matches the GPS' own of being representative only on the country-level. Contextually, it allows insight into how the composition of trade - i.e. whether a bilateral relationship is diversified over several goods classes or restricted to only a few - is affected by preferences or their bilateral distances.

For these purposes, and to retain coherence with the intensive margin estimates, the extensive margin is defined as a count variable of bilateral non-zero trade flows on the three-digit SITC industry level c: $T_{ij} = \sum_c t_{cij}$, with: $t_{cij} = 1$, if: $X_{cij} > 0$. T_{ij} thus has a lower bound of 0 and an upper bound of 240, the amount of three-digit industry classifications. As with its intensive margin counterpart, the extensive goods margin is estimated on the aggregate level, for differentiated and for non-differentiated goods classes. In all cases, PPML is used in specifications otherwise identical to those for the intensive margin: [13]

$$T_{ij} = exp\left(|\boldsymbol{z_i} - \boldsymbol{z_j}|\,\boldsymbol{\beta} + S_i + M_j + \boldsymbol{\phi'_{ij}}\boldsymbol{\gamma}\right) + \epsilon_{ij} \tag{4.7}$$

[12] The estimated coefficients for ϕ are chosen as weights, given their implicit information on a variable's significance. This approach also corresponds to Donaubauer *et al.* (2018).

[13] Note that the count variable definition used in the *breadth of trade* extensive margin estimates is closer to an actual Poisson model than the volume speficiation.

4.5 Results

4.5.1 Standard Gravity

The results from estimating the intensive margin of trade via PPML are reported in Table 4.3. Specification (1) is a conventional gravity equation regressing bilateral exports on distance[14], contiguity, colonial relationships, existing regional trade agreements, a shared language and country fixed effects. With the exception of common language (*lng*) the coefficients have the expected directions and are significant at the one percent level at least. The non-significane of common language does not change when using native and spoken language dummies. This result is in line with Melitz and Toubal (2014), who likewise find insignificant language effects when using PPML estimators[15] and whose language data is used in this analysis.

Specifications (2) and (3) incorporate a *bilateral distance in preferences* measure similar to Jaeggi *et al.* (2018) or Spolaore and Wacziarg (2018) regarding values and genetics. This variable is defined as the unweighted average of the l single preference distances: $\text{dpref} = \frac{1}{l}\sum_k^l(|\boldsymbol{z_{ki}} - \boldsymbol{z_{kj}})|$; and thus measures whether preferences affect outcomes simply by being different between partners, which would speak for the overall preferences reflecting or proxying for a simple cultural (dis-)similarity. Such an outcome is not observed as *dpref* is non-significant in both models. Its inclusion does not alter conventional gravity parameters, implying little correlation between these variables and the preferences, given fixed effects.

In specifications (4) and (5), single preference distances are included. Specification (5) also incorporates measures for distance in legal system quality *leg.qlt*[16] and *comleg*, a dummy indicating whether a pair shares the same legal tradition. These are added to insure that the effect of reciprocity is not related to non-performing legal systems which might be conducive to punishing behaviour as a means to compensate for the lack of legal recourse (cf. Herrmann *et al.*, 2008).[17] This separation reveals a highly significant effect of distances in negative reciprocity on the volume of goods exports. A one standard deviation 0.236)[18] increase - e.g. the distance between Czechia and Lithuania -, would decrease the respective trade volume by 12.5% when accounting for legal systems and 14.87% when not.

This result reflects the hypothesis that a distance in negative reciprocity might deter the less negatively reciprocal partner from engaging with a highly negatively

[14]The measure is constructed by taking the natural logarithm of the average distance in kilometres between the most important population centre's of the two countries as calculated in Mayer and Zignago (2011).

[15]Overlap with the colonial relationship dummy may partially explain these results, as both are relatively broad measures for many-faceted conditions and durations of national exposure.

[16]That measure is drawn from the Worldwide Governance Indicator *rule of law* (in levels) using absolute differences, equivalent to the preference distance calculation.

[17]Note that these parameters are significant and conducive to trade, which likely stems from the facts that navigating a system of similar design is easier and that large distances in legal quality imply the presence of one strong legal system within the pair. (The cases when both countries - or none - have a strong legal system are captured by the fixed effects.) Directions and significance also match the analysis by Yu *et al.* (2015), who also use WGI data as a bilateral variable.

[18]Summary statistics for the preference distances are listed in Table 4.7 of the Appendix.

Table 4.3: Estimation of Aggregated Bilateral Exports

	Basic Grav.	Agg. Pref. Dist.	Agg. Pref. Dist	Single Pref. Dist.	Single Pref. Dist.
	(1)	(2)	(3)	(4)	(5)
ldist	-0.60^{***}	-0.60^{***}	-0.59^{***}	-0.61^{***}	-0.59^{***}
	(0.06)	(0.07)	(0.06)	(0.06)	(0.06)
contig	0.42^{**}	0.43^{**}	0.48^{***}	0.42^{**}	0.48^{***}
	(0.15)	(0.15)	(0.14)	(0.14)	(0.14)
colony	0.29^{**}	0.29^{**}	0.32^{**}	0.29^{**}	0.33^{**}
	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
rta	0.28^{**}	0.27^{**}	0.32^{***}	0.29^{**}	0.35^{***}
	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)
lng	0.05	0.03	-0.08	0.04	-0.06
	(0.15)	(0.15)	(0.12)	(0.14)	(0.13)
dpref		-0.20	-0.44		
		(0.38)	(0.30)		
comleg			0.17^{*}		0.15^{*}
			(0.07)		(0.07)
leg.qlt			0.15^{***}		0.15^{***}
			(0.02)		(0.03)
dpati				0.03	-0.16
				(0.12)	(0.10)
drisk				0.36	$0.52^{(\cdot)}$
				(0.27)	(0.28)
dposrec				-0.00	-0.04
				(0.16)	(0.18)
dnegrec				-0.62^{***}	-0.53^{**}
				(0.15)	(0.16)
Observations	5112	5112	5112	5112	5112
Deviance	4785×10^9	4781×10^9	4646×10^9	4683×10^9	4562×10^9
Null Deviance	52347×10^9	52347×10^9	52347×10^9	52347×10^9	52347×10^9
Exp./Imp. FE	YES	YES	YES	YES	YES

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

Notes: The estimation on aggregated bilateral exports, X_{ij}, is conducted via PPML. The variables of interest are the distances in preferences, included as an unweighted average *dpref* in (2,3) and as single variables *dpati, drisk, dposrec, dnegrec* (4,5). A dummy for common legal systems *comleg* and a measure for differences in legal quality *leg.qlt* are included in models (3) and (5) due to their potential impact on negotiations, the channel of interest. Model (1) is a standard gravity equation for comparison. Standard errors are clustered to Importer and Exporter fixed effects.

reciprocal partner due to the latter's insistence on credible and strong punishment. These punishments, especially if unexpected, would raise the risks of a contract from the perspective of the less negatively reciprocal partner and drive him to limit his exposure to that partner; or, if punishment has occured, motivate him to end that contract. In the same vein, the negatively reciprocal partner might execute a "grim trigger"-like strategy and thus end the relationship permanently. Regarding our hypotheses, these adverse effects appear to outmatch the potential commitment effect (or: reduced incentive to deviate) caused by a higher willingness to commit costly punishment.[19]

The distance in risk is also significant, albeit only at the 10% level, with an effect similar in size to that of *dnegrec* when accounting for legal systems.[20] This corresponds to the diversification or risk transformation hypothesis, in that more risk-averse countries would outsource riskier enterprises, preferring to import their produce - and vice versa. This particular match of a more risk-averse and a risk-tolerant partner may facilitate agreement on the form of trade finance contracts because both partners could agree on allocating risk to the less risk-averse side. Given the significance and robustness issues with this result, it needs to be treated with caution.

4.5.2 Differentiated and Non-Differentiated Goods

Expanding on the aggregated results, specification (5) of Table 4.3 is used for an analysis on differentiated and non-differentiated goods, according to the Rauch (1999) specifications on the 3-digit level. That separation yields two sets of comparable trade volumes and produces reasonable results for conventional variables: distance matters more for non-differentiated goods, trade agreements matter more for differentiated goods requiring complex regulation. Legal quality continues to matter, though a common legal system appears insignificant for non-differentiated goods. The latter is likely a result of the more formalized exchanges governing non-differentiated goods trade, which reduce the importance of legal recourse. Also, as in the aggregated specification, the overall preference dimensions remain non-significant.

The results for distances in negative reciprocity and risk become more nuanced, however. The former remains significant and retains the size and direction of the aggregate results, with a slightly stronger effect for non-differentiated goods where switching contracts and partners in response to punishment (or as part of a "grim trigger" strategy) would be easier.

Distance in risk is still significant only on the 10%-level, but also only for differentiated goods, which fits the risk transformation hypothesis as risk transformation can only occur with different risk profiles. If risk-averse players self-select the less volatile differentiated goods, their export markets must be less risk-averse, so as not to select into the same classes. Hence the positive effect and its limitation to differentiated goods. Second, non-differentiated goods can be traded on exchanges, thus reducing the options for less risk-averse players to strike direct bilateral agreements for risk

[19] In line with behavioral and managerial literature, it would have been sensible to distinguish between costly, but rational punishment and acts of revenge, the forms of negative reciprocity, which have been queried by sub-questions for the GPS. Unfortunately, that data is not being provided in the publicly available data set.

[20] Specifically, trade increases by 14% in volume when *drisk* changes by one standard deviation. That deviation is 0.338, equal the distance between Great Britain to Rwanda.

Table 4.4: Estimation of Goods Category-specific Exports

	Differentiated Goods		Non-Differentiated Goods	
	Agg. Pref. Dist.	Single Pref. Dist.	Agg. Pref. Dist.	Single Pref. Dist.
	(1)	(2)	(3)	(4)
ldist	-0.54^{***}	-0.54^{***}	-0.80^{***}	-0.80^{***}
	(0.07)	(0.07)	(0.07)	(0.06)
contig	0.45^{***}	0.45^{***}	0.42^{*}	0.41^{*}
	(0.11)	(0.11)	(0.18)	(0.17)
colony	0.33^{*}	0.38^{**}	0.43^{***}	0.41^{***}
	(0.15)	(0.14)	(0.10)	(0.09)
rta	0.47^{***}	0.50^{***}	0.26^{*}	0.28^{*}
	(0.10)	(0.10)	(0.12)	(0.12)
lng	0.10	0.09	-0.21	-0.19
	(0.15)	(0.14)	(0.18)	(0.20)
comleg	0.24^{***}	0.21^{**}	0.12	0.11
	(0.07)	(0.07)	(0.08)	(0.09)
leg.qlt	0.17^{***}	0.18^{***}	0.16^{**}	0.14^{**}
	(0.04)	(0.05)	(0.05)	(0.05)
dpref	-0.14		-0.30	
	(0.37)		(0.31)	
dpati		-0.19		0.05
		(0.14)		(0.14)
drisk		$0.44^{(\cdot)}$		0.34
		(0.23)		(0.32)
dposrec		$0.31^{(\cdot)}$		-0.14
		(0.18)		(0.21)
dnegrec		-0.46^{***}		-0.55^{*}
		(0.11)		(0.22)
Observations	5112.00	5112.00	5112.00	5112.00
Deviance	2192×10^9	2140×10^9	2784×10^9	2747×10^9
Null Deviance	37598×10^9	37598×10^9	19520×10^9	19520×10^9
Exp./Imp. FE	YES	YES	YES	YES

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

Notes: For this estimation, aggregated bilateral exports are split into differentiated and non-differentiated goods according to Rauch (1999) three-digit SITC classifications. The variables of interest are the distances in preferences, included as an unweighted average *dpref* in (1,2) and as single variables *dpati, drisk, dposrec, dnegrec* (3,4). Standard errors are clustered to Importer and Exporter fixed effects.

transformation purposes[21].

Distances in positive reciprocity have a weakly significant, positive effect on trade volumes for differentiated goods (specification (2) of Table 4.4), whereas there is no effect for non-differentiated goods. The coefficient corresponds to a 9.2% increase in trade per standard deviation (0.31; equal the distance between Austria and the Netherlands). This positive effect likely reflects the stabilising effect of rewards by the more positively reciprocal player towards his partner, for whom this behaviour would be unexpected given his different reciprocity profile, but beneficial. In this dimension, cultural distance appears to have a positive effect on the intensity of trade. This further highlights why the overall distance in preferences is not significant and presents a case wherein contrasting values or preferences might be beneficial to economic exchange.

4.5.3 Impact on Average Barriers

The fixed effects, i.e. the average trade barriers, are extracted from the single preference specifications (2) and (4) of subsection 4.5.2, Table 4.4, to decompose the effects of GPS preferences on trade outcomes. The effects from the separate sets are used due to the substantial observed differences in coefficients between the goods classes.[22] Exporter and importer fixed effects of the two goods specifications are each regressed on average bilateral characteristics relating to the country in question, population and per-capita GDP, a landlocked dummy and the single preferences in their levels. Population *pop* and per-capita GDP *gdpcap* are significant and have the expected positive signs for importers and exporters alike, while being landlocked has an expected negative effect, signaling the higher transport costs arising from lacking ocean access. Average bilateral characteristics are included for consistency in accordance with Head and Mayer (2014) only and cannot be interpreted on their own. The results are shown in Table 4.5.

Preferences only seem to matter for exporters - displayed in specifications (1) and (3). As search costs and risks associated with (international) trade are typically considered to be borne disproportionately by the exporter, his preferences which influence the motivation to trade and the perception of risks would matter more than those of the importer for his behaviour.[23]

Reasonably then, risk-taking is also the dominant preference. The less risk-averse a population is on average[24], the less differentiated goods it exports but the more non-differentiated ones. For patience, the reverse is true: more patient countries export more in differentiated goods and vice versa. Both effects are of similar size, yet risk has a stronger and more robust effect. For differentiated goods, a one standard deviation change in risk-taking (0.302) would lower the average fixed effect (21.7) by 3.35%. This corresponds to a decrease in exports of approximately equal size and a jump from Brazil's risk attitude to Sweden's. The same change implies an increase of

[21] For which they would not have the same valuation as risk-averse players anyway, given their higher risk tolerance.

[22] Second stage estimations for the aggregate bilateral volumes have also been computed, but found to be non-significant, which is understandable given the effect directions observed in Table 4.5.

[23] It must be noted, however, that PPML tends to overstate origin country fixed effects, which might also contribute to the non-significance of the importer fixed effects.

[24] The variables are normalized to the global average in the GPS data. That mean is risk-averse, not risk-neutral.

Table 4.5: Estimation of Fixed Effects Composition

	Second Stage			
	Differentiated Goods		Non-Differentiated Goods	
	Exporter	Importer	Exporter	Importer
	(1)	(2)	(3)	(4)
(Intercept)	20.11^{***}	-0.33	21.76^{***}	-2.82
	(4.62)	(2.86)	(3.95)	(3.19)
avg.char	-0.18	0.16	-0.23	-0.25
	(1.03)	(0.64)	(0.57)	(0.46)
spop	0.04^{**}	0.03^{***}	0.03^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
sgdpcap	0.44^{*}	0.57^{***}	0.78^{***}	0.55^{***}
	(0.20)	(0.13)	(0.15)	(0.12)
landlocked	-1.35^{*}	-0.98^{*}	-1.30^{**}	-0.92^{*}
	(0.64)	(0.40)	(0.48)	(0.39)
patience	$1.93^{(\cdot)}$	-0.31	-1.62^{*}	-0.38
	(1.05)	(0.65)	(0.79)	(0.64)
risktaking	-2.41^{**}	0.33	1.87^{**}	-0.00
	(0.86)	(0.53)	(0.65)	(0.52)
posrecip	0.46	0.28	0.11	0.03
	(0.66)	(0.41)	(0.49)	(0.40)
negrecip	0.77	0.27	-0.07	0.76
	(0.89)	(0.55)	(0.67)	(0.54)
R^2	0.56	0.57	0.50	0.60
Adj. R^2	0.51	0.51	0.44	0.55
Num. obs.	72	72	72	72

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

Notes: The Fixed Effects represent Average Trade Barriers and are estimated via a two-step approach. Exporter and importer fixed effects are extracted from Table 4.4 specifications (2) and (4) and estimated via OLS using unilateral size and location variables, the average bilateral characteristics relating to the country in question and the single preference variables. Columns (1) and (2) show country characteristics for differentiated goods and (3) and (4) for non-differentiated goods. Exporter results are displayed first in each case.

2.28% for non-differentiated goods. Patience yields the opposite result: a one standard deviation increase (0.370: from Brazil to Vietnam) in the preference increases exports of differentiated goods by 3.28%, but decreases those of non-differentiated ones by 2.42%.[25]

Interpreting these results, higher risk-aversion corresponds to an exporter's product mix leaning towards differentiated goods, whereas exporters more willing to incur risks trade more in non-differentiated goods. This corroborates the risk transformation argument for distance in risk since alternative suppliers for differentiated goods are scarcer, providing incentive for risk-averse producers to trade in them. They might also use this trade to protect themselves against the risk of local downturns. Conversely, less risk-averse players would be less interested in such an insurance, explaining the non-significane of *drisk* for the non-differentiated exports, which they are more likely to produce. By this production choice, they could benefit from a risk premiums offered to them for trading in non-differentiated goods, whose suppliers are more easily switched and substituted.[26]

The coefficients for patience align with their underlying long-term considerations or discount factor arguments. Differentiated goods require more up-front investment to produce or trade and involve more complex searches and negotiations with potential partners. Both requires a longer time horizon for the players in question, while non-differentiated goods remove the necessity for search and negotiations by accessing organized exchanges. Additionally, different patience levels allow term transformation, i.e. firms specializing on products maximizing profits for their country's particular time horizons. These foci would differ between nations, netting efficiency and allocation gains from trade, subsequently reinforcing these specializations.

Notably, due to these specializations, gains could be achieved even between partners of similar time preference, thus explaining the non-significance of *dpati*. Capital allotment - based on discount factors - and contract enforcement would seem reasonable channels for these specialization procedures.[27] As illustrated by Nunn (2007), better enforcement implies more trade in goods which are intensive in relationship-specific investments. Patience, as long-term orientation, would be conducive to considering gains from repeated interactions and more elaborate trade networks. The costs for contract enforcement and its design would then become bearable given the expected future gains from engaging in the effort.

4.5.4 Breadth of Trade - The Extensive Margin

Lastly, the extensive goods margin of trade and thus the negotiations establishing economic exchange are observed using the 3-digit Rauch specifications to transform trade volumes into 240 binary choices per country pair. That is: Does country i export good c to country j? Specification (1) of Table 4.6 presents a conventional PPML gravity estimation for the aggregation of these choices. Specification (2) displays the

[25] Given these opposing effects for the two commodity class subsets, it is unsurprising that the preferences would have no significant impact on the fixed effects of total bilateral flows.

[26] It is beyond the scope of this paper to analyse potentially biasing influences of nation-sepcific ressource allotments on trade outcomes.

[27] The latter is especially notable as inclusion of a legal quality variable causes patience to become insignificant. The corresponding results are displayed in Table 4.10.

extensive margin equivalent to subsection 4.5.1, while specifications (3) and (4) are equivalent to subsection 4.5.2. The coefficients and significances for the conventional variables are reasonable and in line with the volume results, except for the (partial) non-significance of contiguity and real trade agreements.[28]

Distances in patience and positive reciprocity appear significant for the breadth of trade between two nations.[29], contrasting with volume results. A one standard deviation increase in *dpati* (0.331, Estonia to France) increases the number of goods categories traded by 9 to 10%. In the case of *dposrec*, traded categories are 3% lower per standard deviation of distance (France and Spain, for example).

This negative effect could reflect the contract-stabilising effect of unexpected rewards to cooperative behaviour by one party, which would intensify existing relationships but not affect the development of new ones. Similarly, the non-significance of *dnegrec* would imply that its negative effect on trade volumes is not based on the threat of punishment, but reduction of exposure in existing contracts.

The positive effect for difference in patience supports term transformation and specialization argument. Likely, the more patient country in a respective pair invests more heavily in his trade network to achieve further specialization gains. If so, countries with higher distances in patience would follow diverging specialization and investment paths, yielding different product sets and thus venues for trade across goods classes.[30][31] This interpretation also coalesces with the observations that high patience reduces (outward) export barriers for differentiated goods and low patience reduces them for non-differentiated commodities (see subsection 4.5.3). Term orientation can therefore

[28]Elaborating on these effects, commonality of language (*lng*) is significant in these PPML classifications, implying that the issue of their non-significance in the volume specifications might be related to the choice of the dependent variable. For example, a common language would ease establishing trade, but not aid in its intensification. As for contiguity, its non-significance and negative coefficient might point to geographic clusters of countries with similar profiles. The partial non-significance for real trade agreements appears related to the presence of legal control variables, which could imply that trade agreements are not effective without legal enforcement. Furthermore, it is not readily apparent why bilateral trade arrangements would expand the amount of goods categories traded. Both partners in negotiations would attempt to improve the terms of trade for their strengths, their specializations and not seek to expand trade into goods categories where neither is specialized or even active. The significance for non-differentiated goods might then simply reflect the higher competitiveness on exchanges through lower tariffs.

[29]In the second stage, only risk is significant and only for exporters of differentiated goods (see Table 4.12), where it retains the positive effect of the average trade barrier analysis. This may showcase the limits of the preferences' influence or that of the breadth of trade approach to PPML.

[30]Note that this also relates to the non-significance of *dpati* in the volume specifications. Due to the increasing specialization, two players of high long-term orientation could still trade goods within categories to their mutual benefit. Thus, their trade need not be smaller in volume than that between one player of higher and one of lower patience levels. On the extensive margin, however, opportunities are greatest for differently patient players as those opportunities are based on different specialization paths. This difference can be observed in the data. Pairs with one highly patient partner trade in twice as many goods categories and around five times the volume as pairs where both partners have low patience. Pairs of two highly patient partners on the other hand trade in 50% more catgories and than those with one highly patient partner and, again, around five times the volume. This also highlights the fact that GDP and patience are highly correlated, which might affect these results with regard to a possible economic development bias inherent in the GPS' patience measure.

[31] *dpati* is agnostic to the direction of the distance and does not capture whether the exporter's or the importer's is higher. However, a dummy variable capturing this information is neither significant nor does it alter results.

Table 4.6: Estimation of the Breadth of Trade

	Basic Grav. (1)	Single. Pref. Dist (2)	Diff. Goods (3)	Non-Diff. Goods (4)
ldist	-0.25^{***}	-0.26^{***}	-0.23^{***}	-0.34^{***}
	(0.04)	(0.03)	(0.03)	(0.04)
contig	-0.07	-0.04	-0.04	-0.08
	(0.08)	(0.07)	(0.07)	(0.08)
colony	0.11^{*}	0.08	0.05	0.15^{**}
	(0.05)	(0.05)	(0.05)	(0.05)
rta	0.01	$0.06^{(\cdot)}$	0.04	0.13^{**}
	(0.03)	(0.03)	(0.03)	(0.04)
lng	0.32^{***}	0.29^{***}	0.29^{***}	0.31^{***}
	(0.06)	(0.06)	(0.06)	(0.07)
comleg		0.10^{***}	0.08^{**}	0.13^{***}
		(0.03)	(0.03)	(0.03)
rld		0.07^{*}	0.08^{*}	0.04
		(0.03)	(0.03)	(0.03)
dpati		0.28^{***}	0.28^{***}	0.31^{***}
		(0.07)	(0.07)	(0.07)
drisk		-0.12	-0.13	-0.11
		(0.08)	(0.09)	(0.09)
dposrec		-0.10^{***}	-0.10^{***}	-0.09^{***}
		(0.02)	(0.03)	(0.02)
dnegrec		0.07	0.07	0.05
		(0.06)	(0.06)	(0.08)
Observations	5112	5112	5112	5112
Deviance	78802.90	73272.30	54961.47	27058.91
Null Deviance	344350.25	344350.25	220156.99	140931.44
Exp./Imp. FE	YES	YES	YES	YES

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

Notes: Breadth of trade is defined as the number of three-digit SITC goods categories with non-zero export values, i.e. $T_{ij} = \sum_c t_{cij}$. The variables of interest are the distances in preferences, included as single variables *dpati, drisk, dposrec, dnegrec* (2). Model (1) is a standard PPML gravity equation for comparison, specifications (3) and (4) estimate differentiated and non-differentiated goods, respectively. Standard errors are clustered to importer and exporter fixed effects.

be seen as a motivation for specialization and trade.

4.6 Robustness

This section addresses three potential robustness issues: potential sampling issues, the definition of the preference variables and the relationship to surveys similar to the GPS.

4.6.1 OECD subset

As mentioned before, economic preferences - and the experiments and questions by which they are measured - might be influenced by the economic situations of the subjects in question. Risk and patience specifically might be linked to the wealth and development path of the country in question beyond relationships covered by GDP per capita or institutional settings. If preferences are linked to economic characteristics, endogeneity could ensue through relationships between them and trade patterns and intensities. To control for this, a subset of all OECD countries also included in the GPS is used. The greater similarity of OECD countries in terms of wealth, institutional quality and societal organisation mitigates the endogeneity risks.[32] On the other hand, it also limits generality of results due to the smaller set of 25 members and if preference distances impact trade differently for less developed nations.[33] Additionally, the distribution of preferences and their distances is significantly different within the OECD set compared to the whole GPS set.[34] Zero trade is also less common - lowered, on aggregate, from 6.5 to 1%, while the average value of bilateral exports is almost four times as high and the extensive goods margin roughly doubles.

Comparing the gravity estimations for GPS and OECD countries, preference distances have stronger effects within the OECD than for the full GPS set - see Table 4.15 and Table 4.16 in the appendix for detailed results. Trust and altruism still non-significant when included. Distance in negative reciprocity is similar in size and direction to the full results, though insignificant for non-differentiated goods. It must be noted, however, that non-differentiated goods trade matters less within the OECD than in the full sample, accounting for 31% of the volume compared to 37% for the full set. The weak effect of distances in risk does not carry over to the OECD set. On the other hand, distance in positive reciprocity has a significant positive impact on volumes, supporting the hypothesis of a beneficial effect from corresponding gestures - e.g. gifts, perceptions of fairness. Within the OECD set, this effect does also carry over to the breadth of trade. Lastly, the distance in patience positively impacts the volume and breadth of bilateral trade, supporting the specialization and term transformation hypothesis: The average level of patience for OECD countries is higher than in

[32]As well as a resulting focus on western nations.

[33]The generality of the OECD robustness check is restricted further by the GPS' definition. As the distributions are normalized to the individual level of the full set, preferences in the OECD set need not follow that same normal distribution. They cannot be computed in the same manner either because non-normalized data is not provided by the GPS.

[34]The distribution of the preferences and distances for the OECD subset is shown in Table 4.13 and Table 4.14 of the appendix, respectively.

the GPS sample, implying a greater drive for specialization which would then provide greater opportunities for gains from trade.

Overall, the results also imply that preferences might matter more in situations where other issues such as strong discrepancies in economic development or the legal systems of the country pair are less relevant. The smaller effects for commonalities in the legal systems and the negative, but barely significant effects of differences in the quality of legal systems support this interpretation.

4.6.2 Alternative Preference Definitions

In addition to the preference levels and absolute distances used in the main analysis, three alternative specifications have been tested: squared preference distances and the minimum and maximum preference values per pair. The results for the corresponding gravity equations, applied to goods category-specific exports, are displayed in Table 4.18 and Table 4.19 of the appendix. In the former case, the effects for distances in negative reciprocity remain similar, while distances in patience and positive reciprocity become (more) significant. Neither effect changes directions. These additional significances are likely a consequence of the inflated value of strong differences due to taking squares.

In the minimum and maximum value cases, negative reciprocity is highly significant. Risk and positive reciprocity remain significant on the 10%-level for differentiated goods. For negative reciprocity, a higher maximum value is associated with a decrease in trading volume, as is a lower minimum value. That is, the larger the distance, the smaller the trade volume, which is equivalent to the results from the main analysis. For risk and positive reciprocity, higher maximum values and lower minimum values increase trading volumes. This likewise fits the overall positive effect for distances observed in the main analysis, thus supporting the risk transformation and negotiation mechanisms. Given this qualitative similarity and the greater difficulty with disentangling effects, this specification is not used in the main analysis.[35]

4.6.3 Relationship with similar surveys

While the GPS is unique in its combination of decision-relevant preferences and experimental validation, some of its contents have been analysed before. The World Values Survey (WVS) (Jaeggi *et al.*, 2018) and the Hofstede Dimensions (Hofstede *et al.*, 2010) report measures for some of the Falk preferences, which are used for robustness checks in this analysis. Additionally, Wacziarg's genetic and religious distances (Spolaore and Wacziarg, 2016, 2018) are used to ascertain their relationship with preferences, controlling for potential links between these traits and preferences. This follows the literature on ancient origins of cultural and societal traits.

[35]The minimum/maximum specifications were also estimated using a dummy approach. Therein, a maximum (minimum) pair preference value is classified as 1 when its value is one standard deviation above (below) the average preference value and 0 otherwise. Using this approach, negative reciprocity extreme values remain significant, while risk and reciprocity lose theirs. Interestingly, patience becomes significant on the 10% level in this approach, with an effect composition similar to negative reciprocity. However, this approach is only suited for analysing extreme distances and thus not useful for the main analysis, but further underlines the robustness of the effect for negative reciprocity.

World Values Survey The World Values Survey is a global study designed to gather information on values and beliefs of different nations. It is a questionnaire containing items relating to the subject's personal and professional life, their beliefs, culture and values, as well as questions on the perceptions of their society. The evaluation includes trust, altruism, risk and time preferences, allowing direct comparison with the GPS. 57 countries of the GPS are also included in the WVS, 47 of them contain all of the items, providing a sufficiently large set for comparison on aggregate volumes. Bilateral distances for these measures are drawn from Jaeggi *et al.* (2018).

The output table can be found in the appendix as Table 4.20. Using mean distance in World Values Survey items instead of the aggregated distance in GPS preferences does not alter the result noted in subsection 4.5.1. Both coefficients are nonnsignificant. When replacing risk and time preferences with their WVS equivalents and adding trust and altruism, WVS time preferences become significant on the 5% level. Risk does not, negative reciprocity remains significant. This discrepancy might result from the reduced sample size, if the reduction is non-random. Depending on a person's (or nation's) material wealth, saving becomes easier and risk-aversion more logical given higher potential losses. This bias might also manifest differently depending on the phrasing of questions or the execution of experiments.

Hofstede Dimensions Geert Hofstede has modelled national culture as a six--dimensional model with the dimensions proposed as basic issues for societal organisation. These dimensions include long-term orientation and uncertainty avoidance, which correspond to patience and risk attitude in the GPS. Due to Hofstede's calculation, only level effects can be analysed. For that purpose, first stage gravity equation without preference distances is estimated to avoid confounding.[36] The fixed effects of that estimation are analysed using the same specification as in subsection 4.5.3, but with the Hofstede measures for patience and risk (see Table 4.21). Of these, only patience is significant, while risk is not. However, the Hofstede sample encompasses only 44 countries instead of the GPS' 72 and its indices are defined much more broadly in terms of values, morale and philosophy, further limiting their accuracy and comparability.

Genetic and Religious Distance Thirdly, the relationship between preferences and other persistent, long-term drivers of cultural characteristics has to be considered, specifically: common origins. To this end, measures for genetic and religious distance from Jaeggi *et al.* (2018) are used. Both aspects can be seen as persistent influences on developing characteristics of any nation's population and their distance relates to the (in-)frequency of interaction between any two nations. If not the causes, they can still be used as proxies for shared history or origins. Table 4.22 shows the detailed results for weighted distances and an alternative definition of these distances using only the dominant genetic or religious "group" within each country. Neither measure affects coefficients or significance of GPS variables.

[36] Doing so does not alter the results for patience and risktaking, stressing that preference levels and distances are distinct effects.

4.7 Conclusion

Reciprocity as well as term and risk transformation considerations appear to influence bilateral trade outcomes through the mechanism of negotiation. In affirmation of this channel, effects are stronger, more numerous and more pronounced for differentiated goods which are more negotiation-heavy than standardized or exchange-traded goods. Term and risk preferences provide the incentives for trading goods to permit preference-suitable specialization, whereas reciprocity affects the longevity and intensity of the contractual relationship.

Distances in negative reciprocity in particular adversely impact trade volumes. This supports the dual hypothesis that the punishment costs and risks associated with a more negatively reciprocal partner coerce a less negatively reciprocal partner towards limiting his exposure, while the execution of that punishment up to a "grim trigger"-like strategy might terminate deals permanently. Conversely, distances in positive reciprocity intensify trade relationships, aligning with the hypothesis that unexpected rewards or gifts for cooperative behaviour by the more positively reciprocal player would be appreciated by their partner, strengthening the relationship.

Time and risk preferences appear to impact trade outcomes through transformation mechanisms. That is, investment, production and trade patterns are subject to different risks and amortization cycles, inducing higher complexity into negotiations. This prompts players to self-select into products suiting their own preferences in these regards, if given the chance. These selections then lead to specializations, providing comparative advantage and opportunity for trade. Consequently, countries with populations leaning towards risk-aversion and patience export more differentiated and less homogeneous goods, reflecting the higher effort associated with establishing their production and the greater difficulty, for their partner, to change suppliers. Moreover, distances in patience correspond to trading in more product categories, reflecting the growth in trading opportunities between differently specialized partners.

While we cannot speak of causal inference, term, risk and reciprocity attitudes present an intriguing approach towards explaining certain anomalies in trade flows and behaviours not covered by conventional theory. This approach joins the literature strands on trade, behavioural economics and contracts with one another, tying trade outcomes to the people deciding upon their design. At this intersection, further research questions unfold. The causes and directions of the relationship between risk and patience on one hand and GDP and institutional quality on the other as observed in the gravity models would be one example. Another issue is the potential difference in the effects of negative reciprocity between revenge and costly, but rational punishment, which is as of yet not sufficiently distinguished by the GPS data.

That said, this analysis suggests that behavioural leanings can express themselves in trade outcomes and outlines a mechanism through term and risk optimisation on one hand and negotiation on the other by which these outcomes manifest. In contrast to cultural distances, this relationship is not constrained to differences reducing trade. In terms of policy implications, they define limits to the effects of infrastructure, institutions and political action, including trade agreements. At the same time, term and risk transformation as further specialization factors and thus sources for gains from trade could add another dimension to trade negotiations and the perspectives with which their outcomes are judged. With regards to negative reciprocity and the risk of punishment, supranational mediators for trade disputes might be able to alleviate concerns of both sides by delegating punishment to a neutral and transparent court, increasing predictability of the process.

Appendix C

Export Substitutes for Import Data

Eight countries had not reported any data by the time the data was downloaded. These missing entries were replaced with existing export data by their reporting partner nations. This method is potentially biased due to the complete lack of data on trade between these eight countries and potential reporting errors with regards to the traded volumes. While the former issue cannot be addressed with the data available, the latter issue can be investigated by comparing export and import flows of all countries within the GPS set that do report their foreign trade. For these countries, average exports and imports to all other reporting countries in the set are computed as well as standard deviations for these flows. The two resulting distributions can then be tested against the null hypothesis of being drawn from the same population by conducting Kolmogorov-Smirnov tests. That null hypothesis cannot be dismissed for the two- or either one-sided test. Given these results, the export data can thus be used as replacement for imports of non-reporting countries.

For robustness, all estimates have also been conducted for a subset including reporting countries only. In these estimations, all effects grow in significance and size in the extensive margins. In the intensive margin, patience and its distance become less pronounced or even non-significant, while the effect of risk becomes slightly stronger in distances and levels.

Table 4.7: Summary Statistics for Distances in Preferences

Statistic	Mean	St. Dev.	Min	Max	Top 2	Bottom 2
dpati	0.415	0.331	0.0001	1.684	NIC-SWE, RWA-SWE	ITA-JPN, IND-PER
drisk	0.338	0.273	0.0001	1.763	PRT-ZAF, NIC-ZAF	GTM-UKR, ISR-KEN
dposrec	0.382	0.298	0.0005	1.608	EGY-MEX, GEO-MEX	CRI-IDN, POL-ZWE
dnegrec	0.309	0.236	0.00002	1.228	GTM-HRV, HRV-MAR	BRA-KAZ, ARG-VNM
dpref	0.358	0.124	0.061	0.812	GEO-SAU, EGY,ZAF	AUS-CAN, AUT-CHE

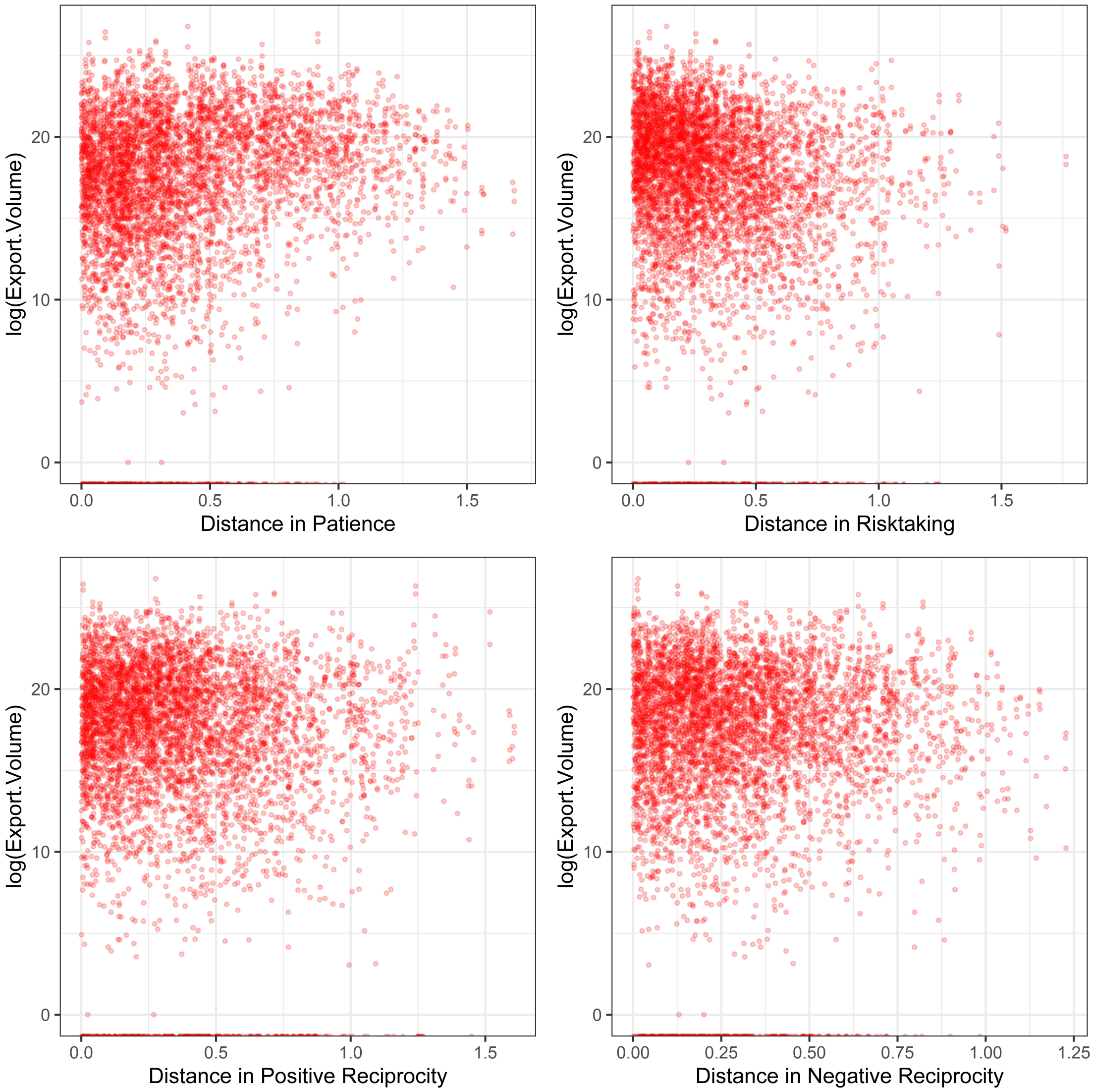
Notes: Summary Statistics for Distances in Preferences. These are calculated as the absolute distance between the two values of each pair. For each preference, the two country pairs with the highest and lowest distance values are provided in order.

Table 4.8: Summary Statistics for Trade on Goods category level

Statistic	N	Mean	St. Dev.	Min	Max
Trading	1,261,440	0.360	0.480	0	1
Volume	1,261,440	8,935,006.000	228,039,017.000	0	74,214,173,234

Notes: *Trading* is a dummy variable which takes value 1 when a specific goods category is traded between a given country pair and 0 otherwise. *Volume* is the volume exported from one country to a specific partner country. For each variable, key distributional statistics are provided.

Figure 4.2: Preference Distance and Export Volume



Notes: Relationship between the natural logarithm of unidirectional exports and GPS preference distances for all country pairs in the GPS for which trade volumes can be computed.

Table 4.9: Summary Statistics for Bilateral Trade Outcomes

Statistic	N	Mean	St. Dev.	Min	Max
Volume (in mio.$)	5,256	2,144.40	11,944,18	0	425,430.22
Trade Links	5,256	86.317	71.344	0	224
Avg. Exp. Partner	5,256	67.342	5.756	47	72
Avg. Imp. Partner	5,256	67.342	5.990	48	72

Notes: Volume is the average value of goods exported from country i to country j for all countries in the set. *Trade Links* is the average number of goods exported from i to j, again for all country pairs. *Avg. Exp. Partner* and *Avg. Imp. Partner* denote the average number of partners for a given exporter and importer, respectively.

Table 4.10: Robustness Estimations of Exporter Fixed Effects - Differentiated Goods

	Baseline	Single Pref.	Single Pref. Rights	Single Pref. Legal
(Intercept)	22.97***	19.30***	19.17***	18.24***
	(4.49)	(4.66)	(5.07)	(4.74)
avg.char	0.64	−0.35	−0.58	−0.63
	(1.02)	(1.07)	(1.05)	(1.10)
pop	0.05***	0.04**	0.04***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)
gdpcap	0.78***	0.43*	0.43·	0.28
	(0.12)	(0.21)	(0.22)	(0.25)
landlocked	−1.63*	−1.41*	−1.44*	−1.35*
	(0.65)	(0.67)	(0.67)	(0.67)
patience		1.86·	0.63	1.51
		(1.06)	(1.15)	(1.10)
risktaking		−2.25*	−1.49	−2.06*
		(0.90)	(0.94)	(0.91)
posrecip		0.97	0.91	0.91
		(1.08)	(1.06)	(1.08)
negrecip		0.64	1.41	0.73
		(0.89)	(0.91)	(0.89)
altruism		−0.84	−0.90	−0.70
		(1.02)	(1.01)	(1.02)
trust		0.46	0.89	0.47
		(0.91)	(0.94)	(0.91)
‘PR Rating‘			0.88·	
			(0.46)	
‘CL Rating‘			−1.24*	
			(0.48)	
Free			0.13	
			(1.90)	
PartFree			0.43	
			(1.14)	
rle				0.48
				(0.42)
R^2	0.50	0.57	0.62	0.58
Adj. R^2	0.47	0.50	0.53	0.50
Num. obs.	72	72	72	72

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

Notes: The Fixed Effects represent Average Trade Barriers and are estimated via a two-step approach for differentiated-goods only. Exporter fixed effects are extracted from Table 4.4 specification (2) and estimated via OLS using unilateral size and location variables, the average bilateral characteristics relating to the country in question and the single preference variables including altruism and trust. Column shows a regression on conventional country characteristics. (2) adds the single preferences in level, (3) and (4) add different institutional and legal quality controls. The results imply a relationship between risktaking and patience on one side and legal regimes on the other. However, these regressions must be treated with caution due to the high number of coefficients.

Table 4.11: Robustness Estimations of Exporter Fixed Effects - Non-Differentiated Goods

	Baseline	Single Pref.	Single Pref. Rights	Single Pref. Legal
(Intercept)	19.34^{***}	20.55^{***}	21.65^{***}	21.30^{***}
	(3.86)	(4.05)	(4.41)	(4.13)
avg.char	-0.63	-0.39	-0.51	-0.27
	(0.56)	(0.59)	(0.61)	(0.61)
pop	0.03^{**}	0.03^{***}	0.03^{***}	0.03^{***}
	(0.01)	(0.01)	(0.01)	(0.01)
gdpcap	0.53^{***}	0.75^{***}	0.71^{***}	0.85^{***}
	(0.09)	(0.16)	(0.18)	(0.19)
landlocked	-1.18^{*}	-1.31^{*}	-1.36^{*}	-1.35^{*}
	(0.49)	(0.51)	(0.53)	(0.51)
patience		-1.60^{*}	-1.41	-1.38
		(0.80)	(0.90)	(0.83)
risktaking		1.96^{**}	1.95^{*}	1.83^{*}
		(0.68)	(0.74)	(0.69)
posrecip		0.26	0.21	0.28
		(0.82)	(0.83)	(0.82)
negrecip		-0.20	-0.36	-0.26
		(0.68)	(0.72)	(0.68)
altruism		-0.50	-0.43	-0.59
		(0.77)	(0.80)	(0.77)
trust		0.84	0.58	0.84
		(0.69)	(0.74)	(0.69)
‘PR Rating‘			-0.36	
			(0.36)	
‘CL Rating‘			0.13	
			(0.38)	
Free			-1.50	
			(1.49)	
PartFree			-1.30	
			(0.89)	
rle				-0.30
				(0.32)
R^2	0.43	0.52	0.54	0.53
Adj. R^2	0.39	0.44	0.43	0.44
Num. obs.	72	72	72	72

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

Notes: The Fixed Effects represent Average Trade Barriers and are estimated via a two-step approach for non-differentiated-goods only. Exporter fixed effects are extracted from Table 4.4 specification (2) and estimated via OLS using unilateral size and location variables, the average bilateral characteristics relating to the country in question and the single preference variables including altruism and trust. Column (1) shows a regression on conventional country characteristics. (2) adds the single preferences in level, (3) and (4) add different institutional and legal quality controls. The results imply a relationship between risktaking and patience on one side and legal regimes on the other. However, these regressions must be treated with caution due to the high number of coefficients.

Table 4.12: Estimation Fixed Effects Composition for Breadth of Trade

	Differentiated Goods		Non-Differentiated Goods	
	Exporter	Importer	Exporter	Importer
	(1)	(2)	(3)	(4)
(Intercept)	4.76^{*}	-1.11	$4.18^{\cdot}$	-1.07
	(1.91)	(0.84)	(2.15)	(1.09)
avg.char	-0.25	-0.49	-0.30	-0.29
	(0.99)	(0.44)	(0.74)	(0.37)
spop	0.01^{**}	0.00^{**}	0.02^{***}	0.01^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
sgdpcap	0.18^{*}	0.08^{**}	0.24^{**}	0.12^{**}
	(0.07)	(0.03)	(0.08)	(0.04)
landlocked	-0.56^{*}	-0.09	$-0.48^{\cdot}$	-0.20
	(0.21)	(0.09)	(0.25)	(0.13)
patience	0.28	0.04	0.25	0.04
	(0.35)	(0.15)	(0.41)	(0.21)
risktaking	$-0.51^{\cdot}$	0.05	-0.26	0.04
	(0.28)	(0.12)	(0.33)	(0.17)
posrecip	0.14	-0.09	0.08	-0.01
	(0.22)	(0.10)	(0.26)	(0.13)
negrecip	0.36	0.05	0.23	0.19
	(0.29)	(0.13)	(0.34)	(0.17)
R^2	0.52	0.37	0.52	0.46
Adj. R^2	0.45	0.27	0.44	0.37
Num. obs.	72	72	72	72

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

Notes: The Fixed Effects represent Average Trade Barriers and are estimated via a two-step approach. Exporter and importer fixed effects are extracted from Table 4.6 specifications (2) and (4) - for differentiated and non-differentiated goods - and estimated via OLS using unilateral size and location variables, the average bilateral characteristics relating to the country in question and the single preference variables. Columns (1) and (2) show country characteristics for differentiated goods and (3) and (4) for non-differentiated goods. Exporter results are displayed first in each case.

Table 4.13: OECD Subset: Preference Distribution

Statistic	N	Mean	St. Dev.	Min	Max
patience	25	0.317	0.416	−0.431	1.071
risktaking	25	−0.078	0.232	−0.792	0.244
posrecip	25	−0.073	0.284	−1.038	0.316
negrecip	25	0.101	0.277	−0.375	0.665
altruism	25	−0.148	0.341	−0.940	0.406
trust	25	0.021	0.260	−0.519	0.532

Notes: The single preferences are normalized to the individual level for the whole GPS sample, while the averages are calculated using only those GPS countries which are also in the OECD. For this reason, the means deviate from zero despite the normalization.

Table 4.14: OECD Subset: Sumary Statistics for Distances in Preferences

Statistic	N	Mean	St. Dev.	Min	Max
dpati	600	0.485	0.332	0.0001	1.502
drisk	600	0.249	0.214	0.001	1.036
dposrec	600	0.296	0.272	0.004	1.354
dnegrec	600	0.321	0.224	0.001	1.040
daltr	600	0.386	0.290	0.002	1.346
dtrus	600	0.297	0.217	0.001	1.051
dpref	600	0.339	0.130	0.061	0.712

Notes:

Table 4.15: OECD Subset: Standard Gravity

	Basic Grav. (1)	Agg. Pref. Dist. (2)	Agg. Pref. Dist (3)	Single Pref. Dist. (4)	Single Pref. Dist. (5)
ldist	-0.52^{***}	-0.55^{***}	-0.56^{***}	-0.60^{***}	-0.60^{***}
	(0.08)	(0.08)	(0.08)	(0.06)	(0.06)
contig	0.69^{***}	0.64^{***}	0.63^{***}	0.66^{***}	0.66^{***}
	(0.15)	(0.14)	(0.14)	(0.12)	(0.13)
colony	0.27^{*}	$0.23^{\cdot}$	0.19	0.28^{**}	0.24^{*}
	(0.13)	(0.12)	(0.12)	(0.11)	(0.11)
rta	0.56^{***}	0.52^{***}	0.50^{***}	0.49^{***}	0.47^{***}
	(0.13)	(0.12)	(0.12)	(0.11)	(0.11)
lng	0.07	0.23	-0.03	0.09	-0.08
	(0.19)	(0.17)	(0.18)	(0.17)	(0.18)
dpref		0.94	1.37^{*}		
		(0.58)	(0.56)		
comleg			0.31^{***}		0.21^{*}
			(0.08)		(0.09)
leg.qlt			-0.05		-0.11
			(0.13)		(0.12)
dpati				0.39^{*}	0.57^{***}
				(0.17)	(0.15)
drisk				-0.26	-0.32
				(0.59)	(0.62)
dposrec				1.24^{***}	1.25^{***}
				(0.30)	(0.32)
dnegrec				-0.66^{***}	-0.52^{***}
				(0.10)	(0.11)
Observations	600	600	600	600	600
Deviance	1067×10^9	1043×10^9	1006×10^9	9215×10^9	9031×10^9
Null Deviance	137327×10^9	13732×10^9	13732×10^9	13732×10^9	13732×10^9
Exp./Imp. FE	YES	YES	YES	YES	YES

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

Notes: The estimation of aggregated bilateral exports X_{ij} of all members of the OECD included in the GPS dataset is conducted via PPML. The variables of interest are the distances in preferences, included as an unweighted average *dpref* in (2,3) and as single variables *dpati, drisk, dposrec, dnegrec* (4,5). Commonalities in legal systems are included in models (3) and (5) due to their potential impact on negotiations, the channel of interest. Model (1) is a standard gravity equation for comparison. Standard errors are clustered to Importer and Exporter fixed effects.

Table 4.16: OECD Subset: Differentiated & Non-Differentiated Goods

	Differentiated Goods		Non-Differentiated Goods	
	Agg. Pref. Dist.	Single Pref. Dist.	Agg. Pref. Dist.	Single Pref. Dist.
	(1)	(2)	(3)	(4)
ldist	-0.46^{***}	-0.49^{***}	-0.81^{***}	-0.86^{***}
	(0.08)	(0.07)	(0.09)	(0.09)
contig	0.59^{***}	0.62^{***}	0.70^{***}	0.72^{***}
	(0.15)	(0.13)	(0.17)	(0.15)
colony	0.21	0.26^{*}	$0.24^{\cdot}$	0.30^{*}
	(0.14)	(0.12)	(0.12)	(0.12)
rta	0.64^{***}	0.62^{***}	0.26	0.19
	(0.14)	(0.13)	(0.16)	(0.16)
lng	0.04	-0.01	-0.19	-0.27
	(0.22)	(0.20)	(0.20)	(0.19)
comleg	0.28^{***}	0.19^{*}	0.43^{***}	0.33^{***}
	(0.08)	(0.09)	(0.06)	(0.10)
leg.qlt	-0.03	-0.11	-0.07	-0.07
	(0.14)	(0.12)	(0.12)	(0.14)
dpref	1.17^{*}		1.58^{*}	
	(0.54)		(0.69)	
dpati		0.57^{**}		0.53^{***}
		(0.18)		(0.15)
drisk		-0.23		-0.85
		(0.56)		(0.73)
dprec		1.14^{***}		1.48^{***}
		(0.33)		(0.34)
dnrec		-0.62^{***}		-0.31
		(0.09)		(0.22)
Observations	600.00	600.00	600.00	600.00
Deviance	716×10^9	639×10^9	397×10^9	366×10^9
Null Deviance	9691×10^9	9691×10^9	4702×10^9	4702×10^9
Exp./Imp. FE	YES	YES	YES	YES

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

Notes: Bilateral exports are estimated separately for differentiated and non-differentiated goods, which are partitioned using Rauch (1999) three-digit SITC classifications. The variables of interest are the distances in preferences, included as an unweighted average *dpref* in (1,2) and as single variables *dpati, drisk, dposrec, dnegrec* (3,4). Standard errors are clustered to Importer and Exporter fixed effects.

Table 4.17: OECD Subset: Breadth of Trade

	Basic Grav.	Single. Pref. Dist	Diff. Goods	Non-Diff. Goods
	(1)	(2)	(3)	(4)
ldist	-0.09^{**}	-0.09^{**}	$-0.04^{\cdot}$	-0.16^{***}
	(0.03)	(0.03)	(0.02)	(0.04)
contig	-0.09^{*}	-0.08^{*}	$-0.07^{\cdot}$	-0.13^{*}
	(0.04)	(0.04)	(0.04)	(0.05)
colony	0.09^{*}	$0.07^{\cdot}$	0.05	0.12^{*}
	(0.04)	(0.04)	(0.04)	(0.05)
rta	0.04	0.02	0.00	0.07
	(0.03)	(0.02)	(0.02)	(0.04)
lng	0.06^{**}	0.04	0.04	0.05
	(0.02)	(0.03)	(0.03)	(0.04)
comleg		0.05^{**}	0.03^{**}	0.09^{**}
		(0.02)	(0.01)	(0.03)
leg.qlt		$-0.05^{\cdot}$	$-0.04^{\cdot}$	-0.05^{*}
		(0.02)	(0.03)	(0.03)
dpati		0.16^{**}	0.15^{*}	0.19^{***}
		(0.05)	(0.06)	(0.05)
drisk		-0.10	-0.09	-0.12
		(0.06)	(0.06)	(0.10)
dprec		0.05^{**}	0.01	0.14^{***}
		(0.02)	(0.02)	(0.03)
dnrec		-0.04	-0.03	-0.06
		(0.03)	(0.03)	(0.05)
Observations	600	600	600	600
Deviance	3156.23	3031.38	1730.66	1845.74
Null Deviance	7788.43	7788.43	3449.64	6048.46
Exp./Imp. FE	YES	YES	YES	YES

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

Notes: Breadth of Trade is defined as the number of three-digit SITC goods categories with non-zero export values, i.e. $T_{ij} = \sum_c t_{cij}$. The variables of interest are the distances in preferences, included as single variables *dpati, drisk, dposrec, dnegrec* (2). Model (1) is a standard gravity equation for comparison, specifications (3) and (4) estimate differentiated and non-differentiated goods, respectively. Standard errors are clustered to importer and exporter fixed effects.

Table 4.18: Estimation of Goods Category-specific Exports with squared preference distances

	Differentiated Goods		Non-Differentiated Goods	
	Agg. Pref. Dist.	Single Pref. Dist.	Agg. Pref. Dist.	Single Pref. Dist.
	(1)	(2)	(3)	(4)
ldist	-0.54^{***}	-0.53^{***}	-0.80^{***}	-0.80^{***}
	(0.07)	(0.07)	(0.07)	(0.07)
contig	0.45^{***}	0.45^{***}	0.42^{*}	0.43^{*}
	(0.11)	(0.11)	(0.18)	(0.17)
colony	0.33^{*}	0.36^{*}	0.43^{***}	0.42^{***}
	(0.15)	(0.15)	(0.10)	(0.10)
rta	0.47^{***}	0.52^{***}	0.26^{*}	0.28^{*}
	(0.10)	(0.10)	(0.12)	(0.12)
lng	0.10	0.07	-0.21	-0.20
	(0.15)	(0.15)	(0.18)	(0.19)
comleg	0.24^{***}	0.23^{***}	0.12	0.12
	(0.07)	(0.07)	(0.08)	(0.08)
leg.qlt	0.17^{***}	0.21^{***}	0.16^{**}	0.15^{*}
	(0.04)	(0.04)	(0.05)	(0.06)
dpref	-0.14		-0.30	
	(0.37)		(0.31)	
dpati		-0.23^{*}		0.01
		(0.11)		(0.10)
drisk		0.28		0.40
		(0.26)		(0.35)
dposrec		0.35^{**}		-0.05
		(0.13)		(0.19)
dnegrec		-0.34^{***}		$-0.60^{\cdot}$
		(0.09)		(0.31)
Observations	5112	5112	5112	5112
Deviance	2192×10^{9}	2149×10^{9}	2784×10^{9}	2757×10^{9}
Null Deviance	37598×10^{9}	37598×10^{9}	19520×10^{9}	19520×10^{9}
Exp./Imp. FE	YES	YES	YES	YES

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

Notes: For this estimation, aggregated bilateral exports are split into differentiated and non-differentiated goods according to Rauch (1999) three-digit SITC classifications. The variables of interest are the distances in preferences, included as an unweighted average *dpref* in (1,2) and as single variables *dpati, drisk, dposrec, dnegrec* (3,4), which are the squared differences of the country pair in question. Standard errors are clustered to Importer and Exporter fixed effects.

Table 4.19: Estimation of Goods Category-specific Exports with minimum and maximum preference values of country pairs

	Differentiated Goods		Non-Differentiated Goods	
	Agg. Pref. Dist.	Single Pref. Dist.	Agg. Pref. Dist.	Single Pref. Dist.
	(1)	(2)	(3)	(4)
ldist	-0.54^{***}	-0.54^{***}	-0.80^{***}	-0.80^{***}
	(0.07)	(0.07)	(0.06)	(0.06)
contig	0.45^{***}	0.45^{***}	0.41^{*}	0.41^{*}
	(0.11)	(0.11)	(0.17)	(0.17)
colony	0.38^{**}	0.38^{**}	0.41^{***}	0.41^{***}
	(0.14)	(0.14)	(0.09)	(0.09)
rta	0.50^{***}	0.50^{***}	0.28^{*}	0.28^{*}
	(0.10)	(0.10)	(0.12)	(0.12)
lng	0.09	0.09	-0.19	-0.19
	(0.14)	(0.14)	(0.20)	(0.20)
comleg	0.21^{**}	0.21^{**}	0.11	0.11
	(0.07)	(0.07)	(0.09)	(0.09)
leg.qlt	0.18^{***}	0.18^{***}	0.14^{**}	0.14^{**}
	(0.05)	(0.05)	(0.05)	(0.05)
maxpati	-0.37		0.10	
	(0.28)		(0.28)	
maxrisk	$0.89^{\cdot}$		0.67	
	(0.46)		(0.64)	
maxprec	$0.61^{\cdot}$		-0.28	
	(0.36)		(0.43)	
maxnrec	-0.93^{***}		-1.10^{*}	
	(0.23)		(0.44)	
minpati		0.37		-0.10
		(0.28)		(0.28)
minrisk		$-0.89^{\cdot}$		-0.67
		(0.46)		(0.64)
minprec		$-0.61^{\cdot}$		0.28
		(0.36)		(0.43)
minnrec		0.93^{***}		1.10^{*}
		(0.23)		(0.44)
Observations	5112	5112	5112	5112
Deviance	2139×10^9	2139×10^9	2747×10^9	2747×10^9
Null Deviance	37598×10^9	37598×10^9	19520×10^9	19520×10^9
Exp./Imp. FE	YES	YES	YES	YES

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

Notes: For this estimation, aggregated bilateral exports are split into differentiated and non-differentiated goods according to Rauch (1999) three-digit SITC classifications. The variables of interest are the minimum - (2) and (4) - and maximum - (1) and (3) - preference values of each country pair. Standard errors are clustered to Importer and Exporter fixed effects.

Table 4.20: Estimation of aggregated bilateral exports using World Values Survey

	Agg. Pref. Dist. (1)	Agg. WVS Dist. (2)	Single Pref. Dist (3)	Single WVS Dist. (4)	Joined Dist. (5)
ldist	-0.59^{***}	-0.57^{***}	-0.59^{***}	-0.57^{***}	-0.57^{***}
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
contig	0.48^{***}	0.49^{***}	0.49^{***}	0.54^{***}	0.56^{***}
	(0.14)	(0.15)	(0.14)	(0.15)	(0.14)
colony	0.31^{**}	0.37^{***}	0.34^{***}	0.41^{***}	0.40^{***}
	(0.10)	(0.11)	(0.09)	(0.11)	(0.10)
rta	0.32^{**}	0.39^{***}	0.34^{***}	0.41^{***}	0.41^{***}
	(0.10)	(0.08)	(0.09)	(0.07)	(0.07)
lng	-0.07	-0.03	-0.07	0.09	0.10
	(0.12)	(0.09)	(0.13)	(0.10)	(0.10)
comleg	0.18^{*}	0.15^{*}	0.16^{*}	0.10	0.05
	(0.07)	(0.07)	(0.07)	(0.09)	(0.08)
leg.qlt	0.14^{***}	0.13^{**}	0.15^{***}	0.14^{***}	0.13^{***}
	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)
dpref (All)	-0.31				
	(0.35)				
DWvsMean		1.01			
		(3.59)			
dpati			-0.15		
			(0.10)		
drisk			$0.50^{\cdot}$		
			(0.26)		
dprec			-0.01		0.04
			(0.21)		(0.18)
dnrec			-0.53^{***}		-0.43^{*}
			(0.16)		(0.17)
dtrus			0.09		
			(0.18)		
daltr			-0.09		
			(0.11)		
Dtrust				-0.06	-0.08
				(0.76)	(0.73)
Daltruism				-0.39	-0.47
				(0.60)	(0.65)
Drisk				0.02	-0.15
				(1.47)	(1.33)
Dtimepref				1.27^{*}	1.22^{*}
				(0.56)	(0.53)
Observations	5112.00	3192.00	5112.00	2156.00	2156.00
Deviance	4654×10^9	3702×10^9	4556×10^9	2724×10^9	2703×10^9
Null Deviance	52347×10^9	42633×10^9	52347×10^9	34797×10^9	34797×10^9
Exp./Imp. FE	YES	YES	YES	YES	YES

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

Notes: Models (1) and (3) include the unweighted average of the preference distances and the single preference distances (including altruism and trust), respectively. Models (2) and (4) replace these values with information from the World Values Survey, as defined by Jaeggi *et al.* (2018) for contrast and comparison. In Model (5), the two surveys are joined, with the WVS measures replacing their Falk equivalents.

Table 4.21: Hofstede & GPS

	Second Stage: Exporter			
	Differentiated Goods		Non-Differentiated Goods	
	(1)	(2)	(3)	(4)
(Intercept)	20.80***	16.46**	21.09***	12.40**
	(4.53)	(4.74)	(3.75)	(4.08)
avg.char	−0.03	−1.03	−0.31	−1.59**
	(1.00)	(0.99)	(0.54)	(0.56)
spop	0.04**	0.03*	0.03***	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
sgdpcap	0.46*	0.32**	0.79***	0.41***
	(0.20)	(0.12)	(0.15)	(0.09)
landlocked	−1.46*	−0.11	−1.26**	−0.65
	(0.62)	(0.78)	(0.47)	(0.62)
patience	1.93·		−1.68*	
	(1.04)		(0.78)	
risktaking	−2.21**		1.90**	
	(0.81)		(0.61)	
uai		0.00		0.02
		(0.01)		(0.01)
ltowvs		0.02*		−0.00
		(0.01)		(0.01)
Adj. R^2	0.51	0.35	0.46	0.42
Num. obs.	72	44	72	44

	Second Stage: Importer			
	Differentiated Goods		Non-Differentiated Goods	
	(5)	(6)	(7)	(8)
(Intercept)	21.09***	−7.32*	−1.97	−9.68**
	(3.75)	(3.43)	(3.05)	(3.29)
avg.char	−0.31	−1.41·	−0.12	−1.20*
	(0.54)	(0.72)	(0.44)	(0.45)
spop	0.03***	0.02**	0.04***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
sgdpcap	0.79***	0.35***	0.57***	0.33***
	(0.15)	(0.08)	(0.12)	(0.07)
landlocked	−1.26**	−0.37	−1.00*	−0.50
	(0.47)	(0.56)	(0.38)	(0.50)
patience	−1.68*		−0.35	
	(0.78)		(0.64)	
risktaking	1.90**		0.19	
	(0.61)		(0.50)	
uai		0.01		0.01
		(0.01)		(0.01)
ltowvs		0.00		0.01
		(0.01)		(0.01)
Adj. R^2	0.46	0.38	0.56	0.55
Num. obs.	72	44	72	44

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

Notes: Exporter (1 - 4) and importer (5 - 8) fixed effects are extracted from a gravity regression on differentiated and non-differentiated goods, respectively. That equation is equivalent to specification (1) of subsection 4.5.1 Standard Gravity. The fixed effects are estimated according to subsection 4.5.3 Impact on Average Barriers, but restricted to the preferences patience and risk. Odd-named specifications show the results for GPS data, even ones depict Hofstede dimensions instead.

Table 4.22: Genetics, Religion & GPS

	Single Pref. Dist.	Gen. Dist.		Rel. Dist.	
	(1)	(2)	(3)	(4)	(5)
ldist	-0.59^{***}	-0.69^{***}	-0.68^{***}	-0.59^{***}	-0.60^{***}
	(0.06)	(0.09)	(0.08)	(0.06)	(0.06)
contig	0.48^{***}	0.38^{**}	0.37^{**}	0.48^{***}	0.49^{***}
	(0.14)	(0.13)	(0.13)	(0.13)	(0.14)
colony	0.33^{**}	0.40^{***}	0.39^{***}	0.33^{**}	0.34^{***}
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
rta	0.35^{***}	0.34^{***}	0.33^{***}	0.35^{***}	0.35^{***}
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
lng	-0.06	-0.06	-0.04	-0.06	-0.06
	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
comleg	0.15^{*}	0.15^{*}	0.15^{*}	0.16^{*}	0.16^{*}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
leg.qlt	0.15^{***}	0.14^{***}	0.14^{***}	0.15^{***}	0.15^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
dpati	-0.16	-0.13	-0.14	-0.16	-0.16
	(0.10)	(0.10)	(0.10)	(0.10)	(0.11)
drisk	$0.52^{\cdot}$	$0.48^{\cdot}$	$0.47^{\cdot}$	$0.52^{\cdot}$	$0.51^{\cdot}$
	(0.28)	(0.27)	(0.27)	(0.28)	(0.27)
dposrec	-0.04	0.03	0.01	-0.03	-0.02
	(0.18)	(0.17)	(0.17)	(0.17)	(0.17)
dnegrec	-0.53^{**}	-0.53^{**}	-0.52^{***}	-0.54^{**}	-0.55^{**}
	(0.16)	(0.16)	(0.16)	(0.17)	(0.18)
gendist_weighted		7.92			
		(5.08)			
gendist_plurality			$6.95^{\cdot}$		
			(4.04)		
reldist_dominant				0.04	
				(0.10)	
reldist_weighted					0.26
					(0.29)
Observations	5112.00	4970.00	4970.00	4970.00	4970.00
Deviance	4562×10^9	4495×10^9	4489×10^9	4548×10^9	4542×10^9
Null Deviance	52347×10^9	51781×10^9	51781×10^9	51731×10^9	51731×10^9
Exp./Imp. FE	YES	YES	YES	YES	YES

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

Notes: The aggregated bilateral exports are estimated via PPML. Models (2) and (3) include genetical distances between populations in two different calculations, whereas specifications (4) and (5) include two version of religious distance. Both distances are taken from Spolaore and Wacziarg (2018) and compared to the GPS' preference distances.

Acknowledgments

We are grateful to Gianmarco Ottaviano, Beata Javorcik, Kalina Minova, Andreas Moxnes, participants of the DICE Research Workshop, the Göttinger Workshop "Internationale Wirtschaftsbeziehungen" and the 4th DICE Winter School of applied Microeconomics as well as one anonymous reviewer for helpful comments and suggestions.

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Declaration of Contribution

Hereby, I, Alex Korff, declare that this chapter, entitled "Economic Preferences and Trade Outcomes" is co-authored with Nico Steffen.

I have contributed substantially to the conception of the research project, the collection and preparation of the data, the development of the empirical strategy and the analysis of the results, as well as the writing of the final manuscript including a substantial revision.

Signature of the co-author:

Nico Steffen

Eidesstattliche Versicherung

Ich, Alex Marvin Korff, versichere an Eides statt, dass die vorliegende Dissertation von mir selbstständig, und ohne unzulässige fremde Hilfe, unter Beachtung der "Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Heinrich-Heine-Universität Düsseldorf" erstellt worden ist.

Düsseldorf, den

Unterschrift