Three Empirical Essays on Consumer Behavior and Competition

DISSERTATION

zur Erlangung des akademischen Grades
Doctor Rerum Politicarum (Dr. rer. pol.)
im Fach Volkswirtschaftslehre

eingereicht an der Wirtschaftswissenschaftlichen Fakultät der

Heinrich-Heine-Universität Düsseldorf

von:	Nicolas Wellmann (geb. Karsten), M.Sc.
	geboren am 19.01.1988 in Osnabrück
Abgabedatum:	1. September 2020
Erstgutachter:	Prof. Dr. Justus Haucap
Zweitgutachter:	apl. Prof. Dr. Ulrich Heimeshoff

Dedicated to the strong women in my life,
who inspire me, encourage me and love me,
my mom, my wife and my grandma

Acknowledgements

This thesis was written during my time being a Doctoral Researcher at the Düsseldorf Institute for Competition Economics (DICE) at the Heinrich-Heine-University. My research has benefited from various discussions at DICE, at national and international conferences and from my research stays at the Computer Laboratory of the University of Cambridge.

First of all, I want to thank my supervisors for guiding me throughout my research and writing of my thesis and always with a pinch of humor. I would like to thank Justus Haucap for his trust and for offering me the chance to pursue my doctoral degree at DICE. With his critical comments and by encouraging me to link my research to policy implications he has improved my thesis a lot. I am also very grateful to Ulrich Heimeshoff who has been a reliable adviser for all kinds of issues which arose throughout my research. In particular I would like to thank him for discussions of various econometric issues which have been very helpful to advance with my thesis. Further, I would like to thank the Device Analyzer group of the University of Cambridge for kindly providing access to their data for my research, for inviting me, and various enlightening discussions during my visits. Also I want to thank my co-author Daniel Czarnowske and my colleagues, Shiva Shekhar, Anja Rösner, Phoutsada Khenkitisack, Daniel Brunner and Amrei Stammann, for various stimulating discussions, shared memories on joint activities, and adventurous journeys.

I would like to thank my family and friends for believing in me and encouraging me during this exciting, insightful but also demanding period of time. In particular, I would like to thank my wife for reading endless pages and enduring countless monologues on specific details and trivia of my dissertation. Thank you! Finally, I would like to thank my son for ensuring continuous supply with power and WiFi cables.

Contents

List of Tables

List of Figures

List of Abbreviations

BEREC	Body of European Regulators for Electronic Communications
FD-IV	First-Difference Instrumental Variable
GDPR	General Data Protection Regulation
GSM	Global System for Mobile Communications
GSMA	Global System for Mobile Communications Association
HAC	Heteroscedasticity and Autocorrelation
HHI	Herfindahl Hirschman Index
M&A	Mergers and Acquisitions
MA	Moving Average
MNO	Mobile Network Operator
MVNO	Mobile Virtual Network Operator
OS	Operating System
OTT	Over-the-Top
SSNIP	Small but Significant Non-transitory Increase in Price
VoIP	Voice over IP

Chapter 1

General Introduction

How does consumption of one product affect the consumption of another? Is the demand relationship between these two products complementary or are they substitutes and compete in a joint market? What are consumers willing to pay for certain product features and how to quantify negative externalities from their consumption? How do parameters of market structure like the market concentration or the entry position affect the quality of products? This thesis covers these relevant questions in economics and specifically industrial organization in three empirical essays. These essays contribute to the existing literature on various levels: First, their analysis makes use of rich datasets with very detailed information on different variables. Second, their empirical strategy is based on novel approaches to address challenges in the empirical estimation. Finally, their research questions cover current topics which are relevant beyond the academical debate. Consequently, the results of their analyses hold important policy implications for decision makers in regulation authorities, firms and politics.

The second chapter is titled *"Are OTT Messaging and Mobile Telecommunication an Interrelated Market? An Empirical Analysis"* and is published in *Telecommunication Policy.*[1] It covers OTT messengers such as Facebook and WhatsApp which have gained wide popularity among mobile users while the traffic of text messaging is in strong decline. As such, there is a debate over whether both services are interrelated and constitute a joint product market, which has important implications for the current wave of mergers in the mobile industry and regulation policy. To the best of my knowledge, this work is the first to provide an empirical analysis of how the consumption of OTT messengers affects demand for text messaging and mobile voice services. It makes use of an innovative dataset which includes very detailed information on smartphone usage in Norway and considers a novel approach to address this question which is embedded in the complexity of two-sided markets. Interestingly, my findings suggest that OTT messengers complement demand for traditional mobile telecommunication services for this context. Consequently, from the perspective of competition policy in Norway both markets are interrelated but do not constitute a joint market. Moreover, I find an explanation for why reductions of text messaging usage have been so drastic in some countries and an analogous development for mobile voice is rather unlikely. Finally, the empirical results provide a new perspective on the modeling of consumer utility in communication networks in the theoretical literature.

The third chapter is titled *"What Would Households Pay for a Reduction of*

[1] This paper has been titled in a preliminary version: "OTT-Messaging and Mobile Telecommunication: A Joint Market? - An Empirical Approach"

Automobile Traffic? Evidence From Nine German Cities". Air pollution, accidents, traffic jams - automobiles face in cities increasing skepticism and their future role in transportation is intensely discussed between residents and politicians. This paper quantifies the marginal and non-marginal willingness to pay for a reduction of automobile traffic. By using a new structural approach in a hedonic framework by Bishop and Timmins (2019) we are able to avoid common issues in hedonic studies using instrumental variables.[2] Our analysis is based on data from nine large cities in Germany between 2016 and 2019 and includes 533,402 detailed observations at the apartment level as well as for various points of interest. To the best of our knowledge this is the first paper to conduct this analysis for Germany. We estimate that the non-marginal willingness to pay for a reduction of traffic per household and year ranges by city between €30.3–59.2 for a 10% reduction, €93.8–158.3 for a 20% reduction and €190.6–252 for a 30% reduction. The highest non-marginal willingness to pay for a reduction of traffic is observed in Frankfurt am Main, the lowest in Leipzig. Further, we compute the expected gains for a reduction of traffic at the city level. In addition to the non-marginal willingness to pay for a reduction of traffic, this considers the composition of the road network as well as for the number of households. Accordingly, these expected gains amount to €163,970–1,019,454€ for a 10% reduction, €484,023–3,261,837 for a 20% reduction, and €1,018,240–6,727,148 for a 30% reduction. The highest expected gains for a reduction of traffic is observed in Munich, the lowest in Leipzig.

The fourth chapter is titled *"Market Structure and Mobile Network Quality - An Empirical Analysis"*.[3] What drives network quality in mobile markets? For the ongoing and upcoming auctioning of 5G spectrum this is an important question. Recent findings in the literature suggest that a higher market concentration may actually raise investments into mobile networks. To the best of my knowledge this paper is among the first to analyze how the market structure affects mobile network quality. The analysis is based on quarterly data from 49 mobile network operators (MNO) from 14 European countries between 2011 and 2016. This makes use of different quality measures which are calculated based on 500 million measurements of mobile network quality. My results indicate that a reduction in market players may potentially increase mobile network quality at the firm and at the market level. Furthermore, late entrants seem to provide a higher share of 3G and 4G connections and connections with different minimum speeds than market incumbents. Market

[2]Bishop, Kelly C., and Christopher Timmins. 2019. "Estimating the marginal willingness to pay function without instrumental variables." Journal of Urban Economics 109:66–83.

[3]This paper has been titled in a preliminary version: "Hello, Are You Still There? An Empirical Analysis How Competition Affects Signal Quality in Mobile Networks'.

incumbents seem to provide higher maximum speeds instead.

Chapter 2

Are OTT Messaging and Mobile Telecommunication an Interrelated Market? An Empirical Analysis

2.1 Introduction

There are more than 1.86 billion monthly active users on *Facebook*, 1.2 billion on *WhatsApp* and 1 billion on *Facebook Messenger* (Facebook 2017). These over-the-top (OTT) messengers, which rely on the Internet to provide their services, have gained strong popularity among consumers worldwide. In several countries a change in consumption behaviour was observed in the mobile telecommunication market with significant reductions in the usage and revenues of text messaging services in the past years. For example, consumption of text messaging declined in Germany by -41%, Italy -40% and the UK -15.3% (Bundesnetzagentur 2015, Ofcom 2015, AGCOM 2015).[1] Though, the rise of OTT messengers may provide a reasonable explanation for this development, empirical research on this topic is still quite narrow.

However, the current merger wave in the mobile industry underlines that it is highly relevant to understand how demand for traditional mobile telecommunication services and OTT messengers is related.[2] If OTT messengers are perceived as viable substitutes to traditional mobile telecommunication services by consumers then these may also constrain the market power of firms in the mobile telecommunication market.[3] So, competition authorities need to account for their presence in competition analysis when defining the relevant product market. Failing to account for their competitive constraint in the competitive analysis may lead to an upward bias in the estimation of market power. For the evaluation of M&As this may suggest a too-restrictive assessment of the mobile telecommunication industry in competition policy.

Further implications would concern regulation policy, as various parts of the mobile telecommunication market have been historically under supervision by regulation authorities: This includes, for example, roaming fees and termination rates but also topics in data privacy (European Union 2016a, European Union 2002, Berec 2018). Generally, these regulations are applied to prevent firms from abusing their market power. Against the background of possible competition by OTT messengers there is a question of whether the current regime of regulations are still required for the mobile telecommunication market and to what extend the regulation needs to adapt so that firms with similar market conditions are bound to the same level of regulation.

[1] Numbers refer to 2014, include traffic for MMS for the UK.

[2] Recent examples in the current wave of mergers, some of which were proposed but did not occur, include: H3G Italy /Vimpelcom (2016), TeliaSonera/Telenor (2015), H3G United Kingdom/Telefonica (UK 2015), H3G Ireland/Telefonica IE (2014), Telefonica Germany/E-Plus (2014), H3G Austria/Orange AT (2012).

[3] See also European Commission 1997 and U.S. Department of Justice and the Federal Trade Commission 2010.

This is not only relevant in the context of the General Data Protection Regulation (GDPR) which has recently come into place in the EU (European Union 2016b), it is also important for the current discussion of the upcoming ePrivacy Directive in the EU (European Union 2019).

This paper aims to explore how the usage of traditional telecommunication services is affected by the emergence of OTT messenger services. As such, it provides novel contributions to the literature on mobile telecommunication markets on various levels: First, to the best of our knowledge, this is the first paper to provide an econometric analysis of how the consumption of OTT messengers affects the demand for traditional mobile telecommunication services. Second, we make use of an innovative dataset which includes very detailed information on smartphone usage. Third, we consider a novel approach to address this question which is embedded in the complexity of two-sided markets. Finally, our empirical findings provide a new perspective on the modelling of consumer utility in communication networks in the theoretical literature.

In particular, we employ 79,545 observations of 787 users from Norway which were collected by a personal analytics app – *Device Analyzer* – between 2013 and 2014. To address the problem that OTT messengers typically lack prices for consumers we apply a new method which employs quantities instead of prices in a demand-based approach to infer substitution between traditional mobile telecommunication services and OTT messenger. To be more precise, we control for various demand shifters on the individual level, to isolate the causal effect of OTT messengers on the daily demand for traditional mobile telecommunication services.

Our findings suggest that social and messaging apps complement the demand for text messaging and mobile voice services in that time period in Norway. Raising the average number of interactions with messaging apps by 16 per day increases the number of sent text messages by 1 per day. Lower but positive effects on demand on text messaging are found for the usage of social networks and mobile calls. Consequently, both markets are interrelated but do not constitute a joint market from the perspective of competition policy in Norway. More generally, we identify the different natures of mobile telecommunication services as a key element for explaining why reductions of text messaging traffic have been so drastic in some countries and why an analogous development for phone calls is rather unlikely.

We focus on Norway, as it has been historically fairly advanced in the adoption of telecommunication services. Beginning with the introduction of fixed telephony, Norway experienced a fairly strong user growth making it a countrywide service nearly within a decade (see Holcombe 1911). Later it became the first non-english speaking country, where the predecessor of the Internet, the arpanet, was expended to (see Abbate 2000). Furthermore, Norway was not only involved in the development of the Nordic mobile telephony system, together with Sweden it also became the first to launch a 1G network in Europe (see Gruber 2005, section 2). So, it is not surprising that the rise of mobile services has also been particularly strong in Norway. Already in 2004 mobile penetration in Norway reached about one subscription per capita (see Andersson et al. 2009). Given this background, it is particular interesting to see how the emergence of OTTs has affected the Norwegian mobile telecommunication market and what lessons can be drawn from this.

The remainder of the paper is organised as follows: Section 2 gives an overview of the conventional market definition and their application to mobile telecommunication markets, problems and solutions involved in market definition with OTTs and, finally, the related literature on OTT messengers. Section 3 describes the market context and the data in detail before outlining the econometric model. Section 4 presents the estimation results, several robustness checks and implications for the theoretical literature on modelling consumer utility of telecommunication services. Section 5 discusses the policy implications of the findings and explains how the relationship between both markets is complementary. Section 6 concludes.

2.2 Literature Review

In the literature on mobile telecommunication markets, competition analysis is an important topic, as these markets typically consist of only a few players. In order to determine what drives competition, it needs to be determined which products and geographic areas define a common market. In mobile markets a major emphasis is put on product substitutability, since geographic areas are typically well defined along national borders.[4] For the definition of the relevant market, EU and US authorities typically consider this from a consumer perspective while using the SSNIP-test as an analytical framework (European Commission 1997, U.S. Department of Justice and the Federal Trade Commission 2010).[5][6] This tests for a limited set of products or areas if a small price increase of 5 to 10% is profitable for a hypothetical monopolist.

[4]This corresponds to the allocation of spectrum which typically takes place on a national level. However, this definition along national lines may blur in the future in the EU, due to its political agenda to push for a joint digital market (European Commission 2019) but also as telecommunication firms which already operate on a multinational level.

[5]SSNIP refers to small but significant non-transitory increases in prices.

[6]Substitutability from the supply-side and potential competition are rather considered as complementary evidence in the EU and US (see European Commission 1997 and U.S. Department of Justice and the Federal Trade Commission 2010).

The underlying rationale is that if two products actually belong to a common market then a price increase should induce sufficient customers to switch from one to the other substitute and thus render the price increase unprofitable. A requirement for this test is that products are positively priced, so that own-price and cross-price elasticities of demand can be calculated. Fortunately, past studies on market definition in the mobile telecommunication could typically rely on this.

One strand in this literature focusses on demand relationships between traditional mobile telecommunication services. For example, Grzybowski and Pereira (2008) consider usage data from customer billings in Portugal. They estimate a structural model and observe a complementary demand relationship between text messaging and phone calls. Instead, Y. Kim et al. (2010) find that both services are substitutes based on a structural analysis of customer data from Asia. The paper by Andersson et al. (2009) is very interesting as they provide an explanation for the noted discrepancy in results. They consider aggregate mobile data from Norway for an eight year period between 1996 till 2004. In that they do not only observe that the demand relationship between both mobile telecommunication services is dynamic over time. So, text messaging and voice services turn from substitutes to complements as their network size increases. They also provide an explanation of why this is the case. Accordingly, the previous exchange of information raises consumer demand for further communication, either in response or to exchange with other consumers. However, the authors argue that the type of service which is actually chosen for further communication depends on consumer preferences, if large network effects are present. So, given a user has preferences for text messaging, incoming phone calls may induce this user to respond or communicate with others via text messaging. As a consequence, the demand for phone calls positively affects the demand for text messaging, rendering both products demand complements.

Another large strand of the literature covers substitution from fixed to mobile network services (see, for example, Briglauer et al. 2011 or Caves 2011, and, for a literature review, Vogelsang 2010). A majority of the listed studies identify mobile voice as a substitute for fixed networks, which suggests that mobile networks are causal for their decline. In the analysis a broad set of methodologies is applied, though panel models dominate. Data is used both on the subscriber and usage level. However, Barth and Heimeshoff (2014a) argue that usage data has advantages for the analysis as it already accounts for changes in consumption behaviour prior consumers cancelling their subscriptions (see p. 947).

More recently, studies in this area of research have been extended to cross-country studies as well as other telecommunication services (Barth and Heimeshoff

2014a; Barth and Heimeshoff 2014b; Grzybowski 2014; Grzybowski and Liang 2015; Grzybowski and Verboven 2016; Lange and Saric 2016). For example, Grzybowski and Verboven (2016) use survey data from 27 EU countries between 2005 to 2011 and estimate a discrete choice model. Their findings indicate a significant substitution from fixed to mobile telephony networks which reduced the penetration of fixed lines by 14.1%. However, they also note a significant complementarity if both services are offered by market incumbents as well as between fixed telephony and broadband Internet services. This underlines the complexity of demand relationships between telecommunication services.

Most close to the focus of this analysis is the work by Lange and Saric (2016), though some differences exists. Their study focusses not only on competition between mobile and fixed services but also managed voice over IP (VoIP) services. Their findings suggest strong substitution effects between mobile and fixed networks. However, they do not find substitution effects between fixed networks and managed VoiP services, thus concluding that these form separate markets. For their analysis they use a half-yearly panel data from 25 EU countries between 2006 and 2011 which is analysed using dynamic panel methods. Similar to previous studies, they use price variations to observe demand substitutions between the different services. This is certainly a preferable procedure as it enables a straightforward analysis of substitution effects if products or services are positively priced. But this is not always the case.

Indeed, applying conventional tools for market definition to OTT services is problematic, since these fail to account for their specific market background. Typically, OTT services serve as a platform which connects two sides of a market (Peitz and T. Valletti 2015, p. 897). For example, Facebook is a platform which provides the services of their social network free of charge to users and in return uses their data to sell advertisements in their network to firms. Consequently, demand from two different groups, in this example users and advertisers, depends on each other while Facebook serves as an intermediate which balances the interest of both groups (see also Evans and Noel 2008). Users may be interested in low access fees and fewer advertisements while advertisers may value a large target audience and low advertisement fees. This interdependency does not solely affect demand and profits it also affects pricing decisions by firms (Rochet and Tirole 2003, Armstrong 2006). Hence, in the aforementioned example the introduction of fees for users of Facebook may not only reduce their demand, it may also lower the demand of advertisers as they face a smaller target audience, which may again feedback on the demand of users. Evans and Noel (2008) and Filistrucchi et al. (2014) criticise the application of the conventional SSNIP-test in two-sided markets as the test considers only one side of the market. This may lead to an under- or overestimation in the definition of true market size and thus competition.

To account for the feedback effects of demand in competition analysis, Evans and Noel (2008) and Filistrucchi et al. (2014) propose a modified version of the SSNIP-test which considers changes in profit and total feedback of demand on both sides of the market.[7] Furthermore, they also stress that market definition should be sensitive to circumstances in the market and name an important exception when it should consider only one side of the market. If competition between different firms is only on one side of the two-sided market then the focus of market definition should also correspond to this. In this case this may allow us to circumvent one important hurdle in the market definition of OTT messengers.

Nonetheless, an important question remains of how to analyse the substitution behaviour of consumers absent prices, as typically the case for OTT messenger.[8] In an alternative approach, Dewenter et al. (2017) consider, similar to this paper, quantities instead of prices to define the relevant market. For this purpose they build a theoretical model and then test in a Monte Carlo simulation whether their theoretical predictions correspond to their empirical findings based on data from the magazine market. They find that substitutability is also reflected in the quantities demanded. Consequently, quantities can also be used instead of prices for market definition. Methodically their paper differs in the econometric approach and scope from this paper. They use the aggregate consumption data of potential substitutes, pre-process this with time-series techniques and then calculate correlation coefficients. In contrast, this paper follows, except for using quantities instead of prices, common procedures of demand studies in modelling consumer demand while controlling for various confounding influences. For answering this work's research question, this has the advantage of not only helping to answer whether both products belong to a joint market, it also provides a better understanding of the underlying economic effects which shape the demand for both types of communication services.

Given the mentioned challenges in market definition, it is not surprising that other papers on OTTs typically have another focus in research or apply a different methodology. For example, some papers discuss the disruptive effect of OTTs on the mobile telecommunication market, but rather from a theoretical or descriptive

[7] To be more precise, Evans and Noel (2008) propose a modified version of the critical loss, which is an application of the SSNIP test.

[8] The communication between clients of OTT messengers is typically free of charge. *An exception is WhatsApp* which has charged an annual fee of $ 0.99 cents after the first year though its price effect on demand can be considered as marginal (Web Archive 2017).

perspective. Feasey (2015) applies the Kubler-Ross model, which defines different stages of grief, to describe the strategic response of the mobile telecommunication industry towards OTTs. Accordingly, their reaction has changed from denial to anger and bargaining, before finally accepting this development and adapting their business model to this change. Peitz and T. Valletti (2015) discuss how OTTs have changed electronic communication markets and outlines potential economic implications. Regarding the market definition of text messaging and OTT messengers they argue that an analysis should be based on the substitution effects of consumers, to answer whether these services form a joint market. Stork et al. (2017) explore descriptively the influence of OTTs on mobile telecommunication prices in African countries using price baskets and price indices. Based on case study evidence from South Africa, Kenya and Namibia they argue that cooperation with OTTs may help the mobile industry to sustain their revenues.

Other papers study OTTs empirically, but focus solely on the services itself and do not consider for its implication on traditional mobile telecommunication services. For example, Scaglione et al. (2015) use diffusion models to forecast the growth of social networks in four G7 countries. They observe for all countries that the diffusion of social networks is driven by network effects. Oghuma et al. (2015) explore motivations of consumers to use OTT messengers. They find that users prefer OTT messengers to text messaging, as the former offers enhanced features to users. Though, as the study is based on survey data, it remains unknown if this preference also drives the purchasing decision of consumers and to what extend.

Finally, some papers use data consumption as a proxy for OTT messaging to analyse their effect on the mobile telecommunication market (e.g. Gerpott 2015 or Gerpott and Thomas 2014). However, the interpretation of their findings remains ambiguous. For example, Gerpott (2015) identifies growing mobile data consumption as an explaining variable for the decline of text messaging usage. However, as the author correctly points out, it is unknown whether consumers substitute to OTT messengers or to other app categories instead (Gerpott 2015, p. 821). But this does not provide an answer to whether traditional mobile telecommunication services and OTT messengers form a joint market. Besides that, the growing sizes of web content may also explain increasing mobile data usage.

To the best of our knowledge this paper is the first to provide an empirical analysis of how usage of traditional telecommunication services is affected by the rising popularity of OTT messenger services. This analysis does not only include the investigation of the market relationship between both services but also considers the effects of other drivers on demand for traditional mobile telecommunication services. This paper contributes to the existing literature, by making use of an innovative dataset which includes very detailed information on smartphone usage in Norway. Further it considers a novel approach in market definition to address OTT messengers which are embedded in the complexity of two-sided markets. Given that the successful introduction of text messaging in Norway has been topic in the previous literature and given that Norway has been historically advanced in the adaption of mobile services, it will be interesting to see how this market has been affected by the introduction of OTT messengers.

2.3 Data & Econometric Model

2.3.1 The Dataset

Before we present the dataset we outline the background of the aggregate market development in Norway at the time of the analysis: Figure 2.1 depicts usage of various telecommunication services during the past decade. We observe that text messaging usage grew linearly until its peak in 2009. From that time it stayed fairly constant with a drop in 2013. Phone calls experienced a positive but decreasing growth in the past which may likely stagnate in the future. In contrast, data usage on mobile phones has been exponentially growing, which may also reflect the rising popularity of OTT services in Norway.

Figure 2.2 shows that the composition of total earnings in the market has changed dramatically. Earnings from time-charged traffic and text-messages which account for most of the earnings in 2010, have become a minor driver. Instead, subscriptions and set-up fees account for nearly 65% of the earnings in 2015. This suggests that pricing in the market has moved from usage to access level.

For the analysis, we employ 79,545 observations from 787 users in Norway who made use of a personal analytics app *Device Analyzer* between October 2013 and October 2014. The app is available for the Android operating system (OS) and is offered via the Google Playstore by the Computer Laboratory of the University of Cambridge. Technically, the app makes use of various data which is processed on Android OS. The app takes a full log of all this data with a timestamp and in return provides participants with detailed information on their smartphone usage (see also D. Wagner et al. (2013), D. T. Wagner et al. 2014).

A particular strength of this dataset is that it comprises very detailed information on smartphone usage. This includes, for example, data from sensors such as the current location, the battery state, system settings by users, contacts, connectivity to bluetooth, wifi or mobile networks, which apps are running in the background and

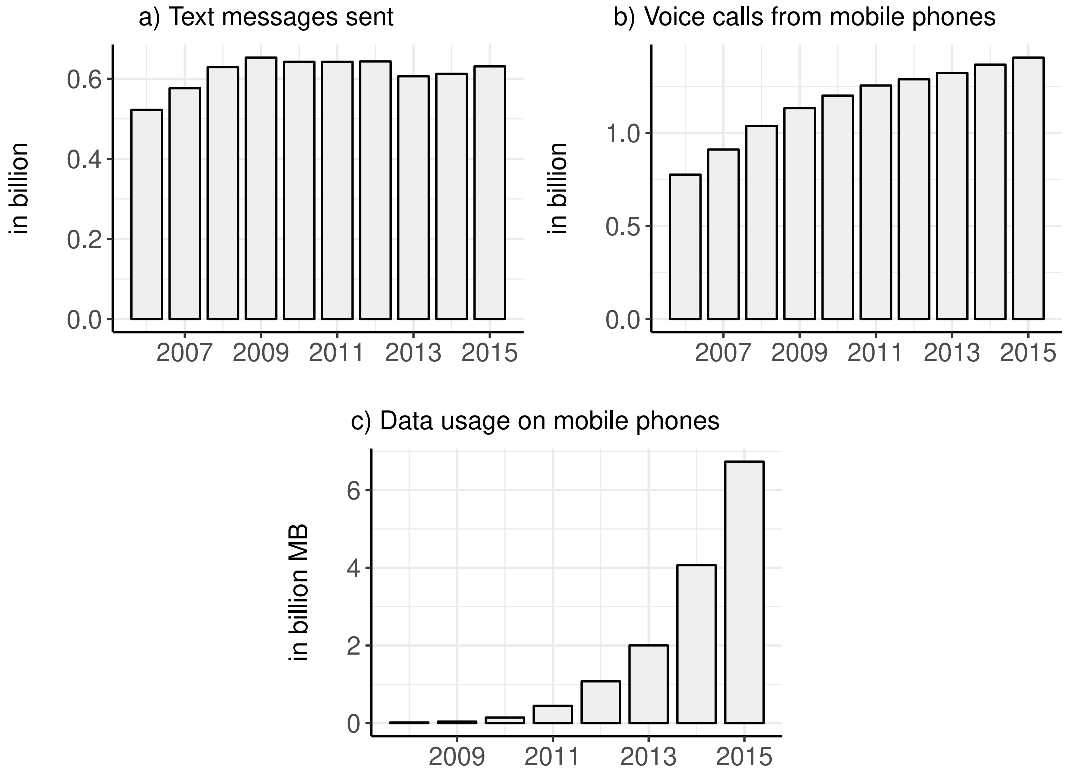

Figure 2.1: *Aggregate Usage of Text Messaging Phone Calls and Data Usage on Mobile Phones in Norway. Own illustration. Data: Norwegian Communications Authority.*

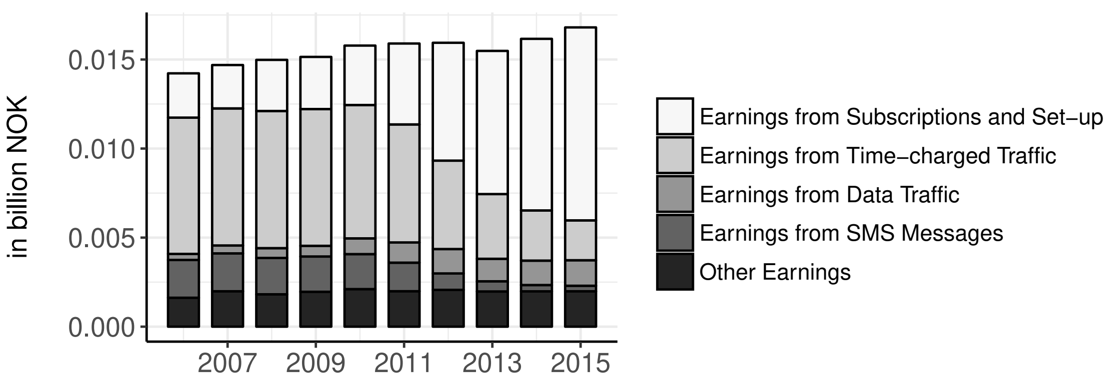

Figure 2.2: *Composition of Earnings in the Norwegian Mobile Telecommunication Market. Own illustration. Data: Norwegian Communications Authority.*

also which have been viewed on the screen and data from incoming and outgoing text messages and phone calls, including their lengths as well as the number of the sending or receiving contact. For the analysis we focus only on that information which is directly related to communication on smartphones. This has been aggregated from the raw data into different variables on a daily basis and grouped for the analysis according to the following criteria:[9]

messenger apps such as *Facebook Messenger* or *WhatsApp* whose design and functionality typically resemble text messaging applications on smartphones. A common feature is the communication with a known set of contacts usually via a contact list.

social apps like *Facebook* or *Google+* which usually involve additional functions to socialise with other people, post elaborate texts or media to groups and which can also be commented on.

Obviously, collecting all these types of data within an app may also raise privacy concerns. For these purposes the developers of the app have taken different measures to ensure that this is maintained. This entails replacing any private information in the dataset with hashes (D. T. Wagner et al. 2014). Not included in the dataset is any information which is processed within apps, such as the content or contacts of exchanged messages in *WhatsApp*. For security reasons access to app data in the internal storage of Android OS is restricted and is only possible for the respective app itself (Google 2018).

Generally, our dataset matches fairly well with the overall trend of mobile phone usage at that time period in Norway depicted in Figure 2.3. Usage of traditional mobile phone services (text messaging and phone calls) varies to some extend on a daily basis, but these variations are fairly constant over time and correspond to the aggregate growth of both services in Figure 2.1. In contrast, aggregate usage of OTT services (messenger and social apps) nearly doubled, which reflects an increasing interest for these services.

Figure 2.4 depicts scatterplots for the different services in the dataset. It suggests a fairly positive relationship within traditional mobile telecommunication services and OTT messengers respectively. A slightly negative relationship is indicated for text messaging and social apps. The demand relationship for other combinations of variables seems to be rather independent as scatterplots do not indicate a systematic pattern for those combinations of variables. Though, in this context it is important to note that scatterplots may only give a rough indication and do not imply anything

[9]An overview of these variables is presented in Table 2.3 of the appendix.

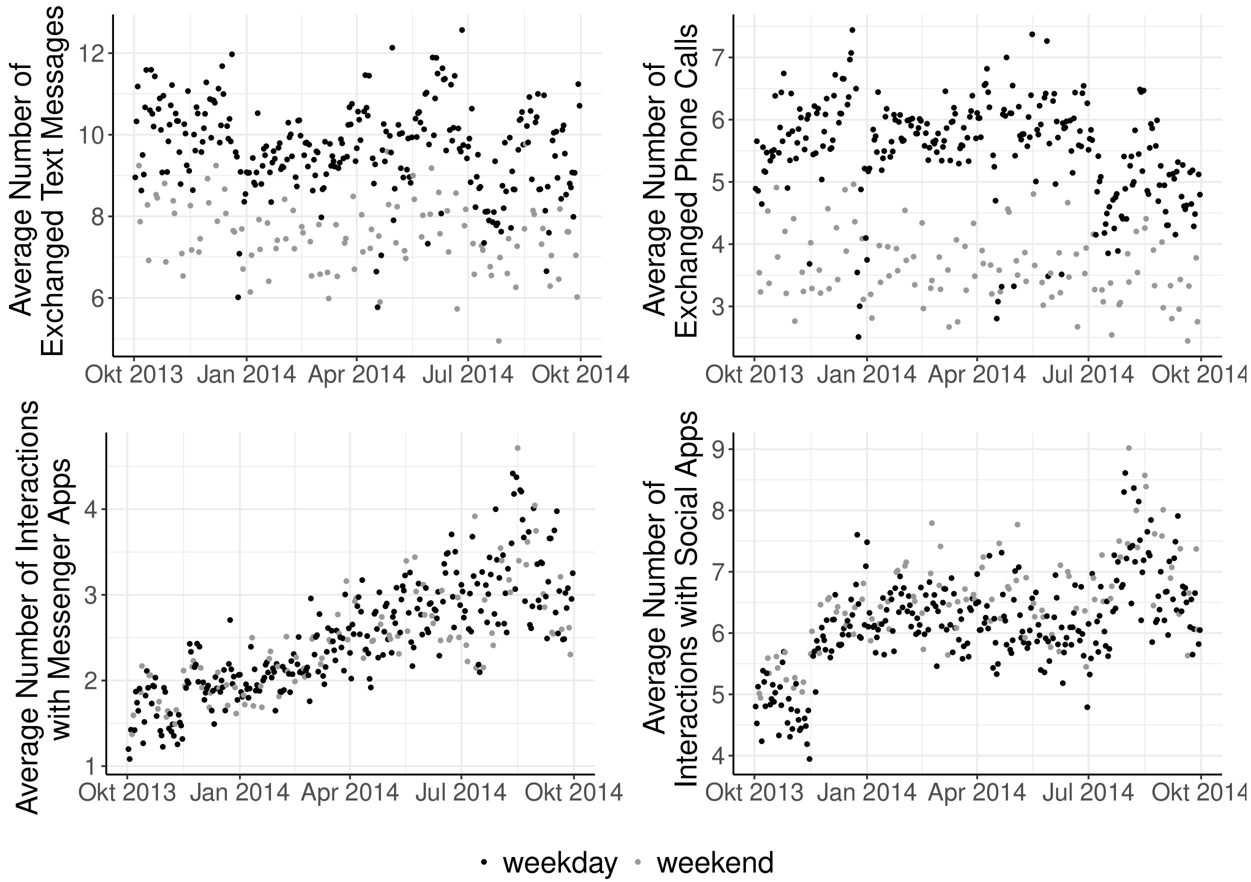

Figure 2.3: *Average Usage of Various Mobile Services per Day by Norwegian Device Analyzer Users between October 2013 and October 2014. Own illustration. Data: Device Analyzer.*

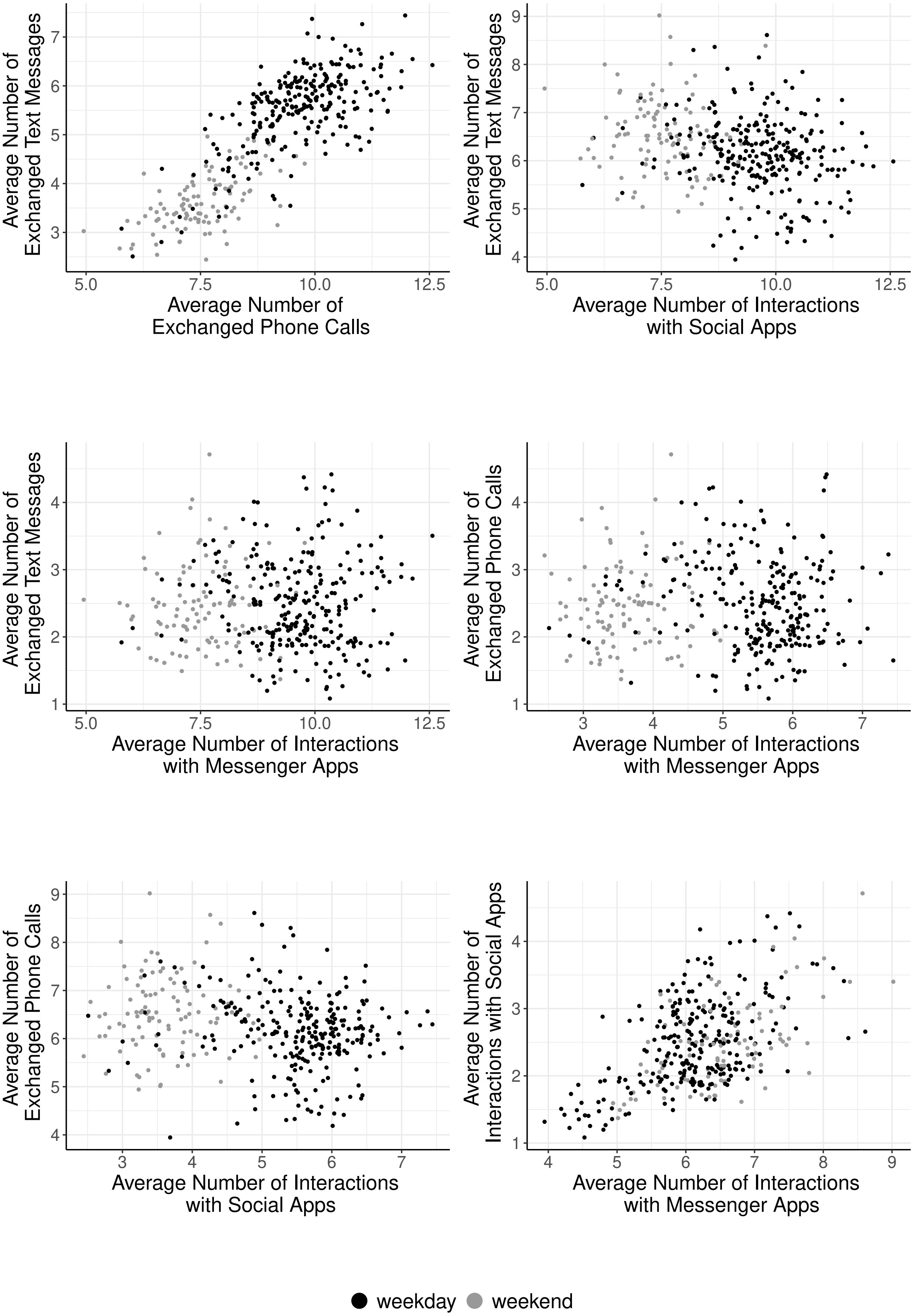

Figure 2.4: *Scatterplots of Average Daily Usage of Text Messaging, Phone Calls, Messenger and Social Apps by Weekday. Own illustration. Data: Device Analyzer.*

about the causal relationship between two variables since these do not include controls for confounding influences. But these controls are added in the econometric analysis.

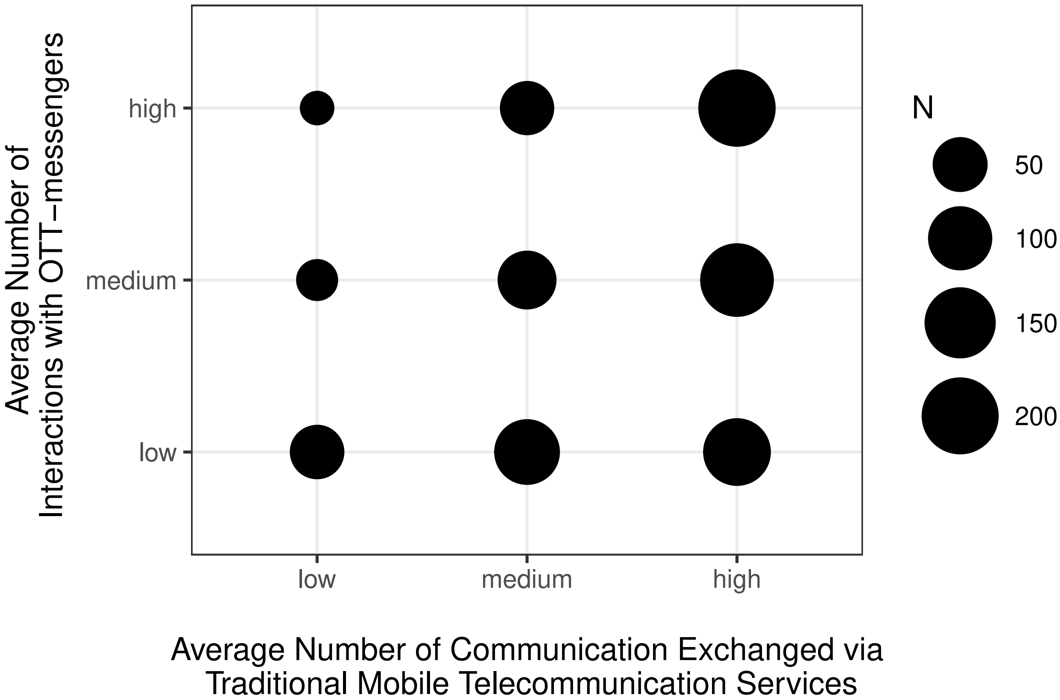

Figure 2.5: *Average Usage Intensity of Norwegian Device Analyzer Users per Day. Traditional mobile telecommunication services refers to text messaging and phone calls. Own illustration. Data: Device Analyzer.*

In the dataset usage of messaging and social apps is quite common among users with shares of 88% and 94%, respectively. Among these the popularity is particularly high for apps by *Facebook* such as *Facebook* itself, *Facebook Messenger* or *WhatsApp*. Other communication or social apps only have a minor importance in the sample. Figure 2.5 depicts an overview of the usage intensity of traditional mobile telecommunication services (text messaging and phone calls) and OTT messengers (messenger and social apps). For these purposes individual usage of participants has been grouped into three evenly large quantiles based on the distribution of usage of the respective services. It can be observed, that the usage of both services or predominantly traditional mobile telecommunication services are common and occur with all types of usage intensities. Less common are users with a high usage of OTT messengers but lower usage of traditional mobile telecommunication services. This fits to the interpretation of Figure 2.1 and Figure 2.3 that usage of traditional mobile telecommunication services is still very present, but usage of OTT messengers is rapidly growing. Furthermore, it becomes obvious that usage varies not only over time, as observed in Figure 2.3, but also across individuals.

2.3.2 Empirical Strategy

OTT messengers like *Facebook* often operate as a platform on two sides of a market, thereby balancing the interest of users and advertisers. Similarly, mobile operators, as an Internet service provider, can also be considered as a platform which balances the interest of their users and content providers (see also Peitz and T. Valletti 2015). As noted in the literature review, market definition should consider the two sides of the market to account for possible interactions between them. However, Filistrucchi et al. (2014) and Evans and Noel (2008) also mention that if two firms do business on two sides of a market but competition between these firms only takes place on one side of the market then market definition should correspond to this. This is the case for the markets in question in this paper: The discussion about mobile operators and OTT messengers focusses on the provision of similar communication services and neither advertising nor the provision of Internet services.

For the two largest OTT messaging services *WhatsApp* and *Facebook Messenger* it may be also questioned whether these operate in two-sided markets, as these were provided without advertisement during the period of analysis. Consequently, we will consider only one side of the market and focus on the substitution of consumers between different communication services to explore whether these form a joint market. For the analysis, we consider usage data of traditional mobile telecommunication services and OTT messengers, since this is likely to be affected by changes in consumption behaviour already even before mobile subscriptions are actually affected (see also Barth and Heimeshoff 2014a).

The specification of the econometric model follows the analysis of current demand studies (e.g. Basalisco 2012, Barth and Heimeshoff 2014b, Lange and Saric 2016) and adapts them to our framework. Precisely, we model demand by considering the influence of potential substitutes as well as from incoming and outgoing traffic and control for various confounding influences on demand. Formally, we aim to estimate the effect of OTT messenger usage on the demand for both technologies $k \in K = \{sms, phone\}$. Thus, demand for technology k is a function of the following variables:

$$Q_k^{out} = f(Q_k^{in}, P^{sub}, N_k, X) \tag{2.1}$$

where Q_k^{out} is the quantity demanded for outgoing and Q_k^{in} the quantity of incoming traffic of technology k, P^{sub} is a price vector of technology k and its potential substitutes with $P = \{\text{sms, phone, messenger, social}\}$, N describes the local network size of technology k and X is a vector of demand shifters.

For the time frame of the analysis we assume that the choice of the mobile contract is given and exhibits a constant effect of prices on mobile phone usage. For other markets this might be quite a strong assumption. However, given the narrow 12-months time frame of the analysis, the daily aggregation of the data and finally the nature of the Norwegian mobile telecommunication market, this is in fact less restrictive. First of all, in the period of the analysis postpaid subscriptions make up for 75% of the contracts in Norway. Thus, a majority of consumers are bound to predetermined conditions for a long-term period. Among all offered contracts in that time period nearly 75% include a fairly high or even unlimited quota for text messaging and voice usage, as becomes apparent in Figure 2.6. At *Telenor*, the largest provider in Norway with a 50% market share, the most popular subscription includes unlimited texts and calls (Norwegian Communication Authority 2015, p. 28f.). Hence, this renders demand fairly rigid with respect to price change, as it may only be affected by further price increases. Therefore, in the analysis price effects are captured via the individual specific effect α_i. However, as roaming fees may differ dramatically under the within-country subscription conditions we account for this by adding the variable R which controls for changes in the roaming status.

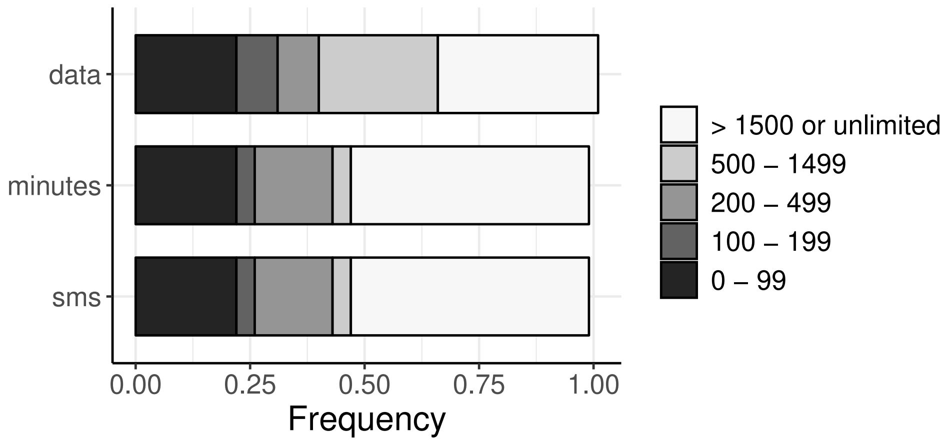

Figure 2.6: *Share of Mobile Contracts of the Four Largest Mobile Providers in Norway which include a Fixed or Unlimited Quota for Text Messages, Phone Calls or Data Services. These providers are namely Telenor, TeliaSonera, Network Norway and Tele2. According to the Norwegian Communication Authority (2015) they accumulated more than 90% of the subscribers in 2014. Source: Company websites, own calculations.*

A particular challenge for the analysis of substitution effects between both types of communication services is that OTT messengers offer their services essentially free of charge.[10] This renders the competition analysis problematic as it typically

[10]The communication between clients of OTT messengers is typically free of charge. *An exception*

relies on prices to infer substitution behaviour of consumers. As a solution to this we propose to use usage levels Q_{kits}^{sub}, both for OTT messengers and mobile telecommunication services in demand analysis to study the effect of potential substitutes s on demand for technology k. In this case, the interpretation is that variations in their consumption reflect ceteris paribus joint changes in the supply conditions of that service. Consequently, when supply conditions change consumer utility this is also likely to affect their usage behaviour. This may, for example include new features or service updates for OTT messengers which are regularly provided, but also increasing network effects due to a rising popularity of these services. Instead, usage of traditional mobile telecommunication services may be driven by lowering network effects due to a decreasing popularity. In the analysis, we are interested in a substitution between technologies of communication services and not between specific services we employ aggregate levels of OTT messenger usage. Though, to account for the heterogeneity among OTT messengers we use the aforementioned categories for messenger and social apps.

Incoming and outgoing traffic has not only been identified as an important driver for demand but, as a confounding element that may also turn substitutes into complements (see section 2.2). Thus, in line with Basalisco (2012) and Andersson et al. (2009) we make use of the disaggregated structure of our dataset and account for the effects of incoming traffic on the demand of technology k. Moreover, we control for the amount of information exchanged as it is likely to have a confounding effect on traffic. This is particularly true for text messaging which can be used either for self-contained messages or as an instant chat.

Network effects may not only exhibit a switching cost to consumers and thus reduce their willingness to substitute (Klemperer 1995), they are also an important driver of demand for telecommunication services (Katz and Shapiro 1985). Our dataset allows us to disentangle whether communication is reoccurring to contacts via text messaging or voice services. We include this information to account for these local network effects on demand and model their magnitude in our estimation. Finally, due to the daily aggregation of the dataset the analysis might be affected by the confounding influences of seasonal effects which have also been observed in Figure 2.3. Thus, time dummies *day* have been added for j days of the week as well as official holidays in Norway.[11]

is WhatsApp which has charged an annual fee of $ 0.99 cents after the first year though its price effect on demand can be considered as marginal (Web Archive 2017).

[11] In particular this encompasses the following list of holidays and events: Christmas: 25, 26 December in 2013; New Year's Eve: 1 January; Mothers Day: 9 February; Valentines Day: 14 February; Easter: 18, 20 and 21 April; Labor Day: 1 May; Norwegian Constitution Day: 17 May; Ascension Day: 29 May; Whitmonday: 8, 9 June; St John's Day: 23 June in 2014.

Taking into account the panel structure of our data and the conditions in the market, we specify the daily demand decision for technology k by consumer i at time t as follows:

$$\begin{aligned} Q^{out}_{kit} &= \alpha_i + \beta_1 Q^{in}_{kit} + \beta_2 I_{kit} + \beta_3 \sum_s Q^{sub}_{kits} + \beta_4 R_{it} \dots \\ & \beta_5 N_{kit} + \beta_6 \sum_j day_t + \beta_7 holiday_t + u_{kit} \end{aligned} \tag{2.2}$$

Based on our data, the variables in our regression are specified as follows: Q^{out}_{kit} measures the quantity of outgoing text messages or calls and analogous Q^{in}_{kit} the ones for incoming traffic, respectively. Since missed calls may trigger consumers to call back, these variables also have information on unsuccessful calls, to include their demand effect. I_{kit} is specified with the average length of text messages in characters and call length in seconds, independent of the direction of communication. $\sum_s Q^{sub}_{kits}$ includes usage of the potential substitutes. For text messaging and phone calls this is simply specified by the usage quantities. For social and messaging apps this measures how often an app of that category has been in the foreground while the screen is on. N_{kit} refers to the number of contacts communication has been exchanged with via text messaging or phone calls. R_{it} counts the frequency of the roaming status being positive during a periodical check.

Given our assumptions and our structural model we have to assume endogeneity for two types of variables. First, incoming and outgoing traffic of technology k may be void to a simultaneity bias. Second, as we expect a substitution effect between the usage of different communication services, we also need to assume that their estimation is subject to a simultaneity bias. This may compromise the causal interpretation of our estimation results. In order to account for this we exploit the time dimension of our panel structure and use lags of the endogenous variables as instruments. This is in line with previous empirical works which have applied these types of instruments for the case of both incoming and outgoing traffic (Basalisco 2012) as well as potential substitutes (Barth and Heimeshoff 2014b).

Furthermore, to account for unobserved heterogeneity and the panel structure of our dataset our model is estimated with the first-differences instrumental variable estimator (FD-IV-estimator). Transforming our model into a first-differences setting yields:

$$
\begin{aligned}
\Delta Q^{out}_{kit} = &\; Q^{out}_{kit} - Q^{out}_{kit-1} && (2.3)\\
\Delta Q^{out}_{kit} = &\; \beta_1 \Delta Q^{in}_{kit} + \beta_2 \Delta I_{kit} + \beta_3 \Delta \sum_s Q^{sub}_{kits} + \beta_4 \Delta R_{it} \ldots && (2.4)\\
&\; \beta_5 \Delta N_{it} + \beta_6 \Delta \sum_j day_t + \beta_7 \Delta holiday_t + \Delta u_{kit}
\end{aligned}
$$

Our dataset contains detailed information on mobile phone usage but is restricted to information at the device level. The FD-IV-Estimator allows us to estimate our model consistently and unbiasedly without including such individual specific information like type of user profile, mobile subscriptions but also looking at other confounding influences on demand, such as age or income. For this purpose the estimator uses changes from variables of different individuals over time instead of the actual level of these variables. Hence, it does not affect the estimation results if usage is generally higher or lower for some service, instead it measures how does the usage of service k varies when usage of substitutes s changes. A requirement for this is that those variables which are unobserved and not included in the model are constant during the period of analysis. But, given the duration of one year this is unlikely to be the case. Other panel estimation techniques, such as the random effects estimator, may allow a more efficient estimation.[12] However, their results turn inconsistent when applied with weakly exogenous instruments (Cameron and Trivedi 2005, p. 758). Thus, these are ruled out as our model relies on lagged instruments. Moreover, as the number of observations is fairly high it is still ensured that estimates are sufficiently precise.

2.4 Empirical Results

2.4.1 Estimation Results

The results of the FD-IV estimation for text messaging and voice are presented in Table 1 and 2 with heteroskedasticity and autocorrelation (HAC) robust standard errors. Respectively, specifications 1) and 2) employ the second lag of the differenced endogenous variable as an instrument, specification 3) uses the third lag instead.[13]

Generally, the results for both demand estimations of text messaging and phone

[12] It is acknowledged that with the first-difference-estimator there is a loss of observations in $t = 1$.

[13] For example, we instrument $\Delta Q^{\hat{in}}_{kit}$ with $\Delta Q^{\hat{in}}_{kit-1}$ and $\Delta Q^{\hat{in}}_{kit-2}$ in specifications 2) and 3) respectively.

calls are in line with economic theory as well as the descriptive statistics in section 2.3.1. So, we find a positive demand effect on text messaging for all potential substitutes. This suggests for the period of analysis that these services rather complement the demand for text messaging services in Norway than substitute it (see Table 2.1). This indicates that demand for OTT messengers and text messaging is interrelated, but does not provide evidence that both services form a joint market from the perspective of competition policy. A similar effect of potential substitutes can also be observed for the demand of phone calls, though with a lower magnitude (see Table 2.2). Furthermore, most of the coefficients are highly significant at the 1% level and we can also reject the H0-Hypothesis of the F-test at the 1% level that the joint effect of the included variables is zero.

	$Q^{out}_{textmessaging}$		
	(1)	(2)	(3)
$Q^{in}_{textmessaging}$	0.527***	0.457***	0.455***
	(0.019)	(0.022)	(0.021)
$Q_{phonecalls}$	0.050***	0.017***	0.020***
	(0.007)	(0.006)	(0.007)
$Q_{messengerapps}$	0.053***	0.050***	0.040***
	(0.010)	(0.009)	(0.010)
$Q_{socialapps}$	0.017***	0.013***	0.009**
	(0.005)	(0.005)	(0.004)
$N_{textmessaging}$		0.493***	0.498***
		(0.041)	(0.040)
$I_{textmessaging}$	−0.007***	−0.011***	−0.011***
	(0.001)	(0.001)	(0.001)
R	−0.001	−0.002	−0.002
	(0.002)	(0.002)	(0.002)
Weekday Dummies	Yes	Yes	Yes
Holiday Dummies	Yes	Yes	Yes
Instruments	2nd lag	2nd lag	3rd lag
F-Statistic	1485	2580	2648
Observations	74,047	74,047	72,111
Adjusted R^2	0.421	0.449	0.450
Note:			*p<0.1; **p<0.05; ***p<0.01 HAC robust standard errors

Table 2.1: *FD-IV Estimation For Text Messaging.*

	$Q^{out}_{phonecalls}$		
	(1)	(2)	(3)
$Q^{in}_{phonecalls}$	0.493***	0.039*	0.019
	(0.022)	(0.022)	(0.022)
$Q_{textmessaging}$	0.027***	0.012***	0.008***
	(0.003)	(0.003)	(0.002)
$Q_{messengerapps}$	0.015***	0.009**	0.001
	(0.006)	(0.005)	(0.004)
$Q_{socialapps}$	0.009**	0.004	0.005
	(0.005)	(0.004)	(0.003)
$N_{phonecalls}$		0.837***	0.855***
		(0.037)	(0.036)
$I_{phonecalls}$	−0.0003***	−0.0003***	−0.0002***
	(0.00002)	(0.00002)	(0.00002)
R	0.006***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)
Weekday Dummies	Yes	Yes	Yes
Holiday Dummies	Yes	Yes	Yes
Instruments	2nd lag	2nd lag	3rd lag
F-Statistic	1192	2923	2350
Observations	74,047	74,047	72,111
Adjusted R^2	0.149	0.366	0.369
Note:			*p<0.1; **p<0.05; ***p<0.01 HAC robust standard errors

Table 2.2: *FD-IV Estimation for Phone Calls.*

In more detail, we observe the strongest effect on text messaging demand for messaging apps among the different communication services (see Table 2.1). Those consumers who interact with messengers an average of 16 times more per day, send on average one additional text message per day. For social apps, we find a lower demand effect of around one-third the size, which might be explained with differences in the design and functionality of both communication services. While messaging apps focus primarily on communication, social apps often provide other functionalities apart from that such as browsing user profiles, reading news articles or public posts from other people.

Apart from other communication services, the results in Tables 2.1 and 2.2 suggest a dominant role of incoming traffic on the demand decision: 10 more incoming text messages increase demand for that service ceteris paribus by 5 per day. Similarly, 10 more incoming phone calls raise demand for that service ceteris paribus by 6 per day. Additionally, increasing the information exchanged in text messages (phone calls) by 83 characters (41 minutes) reduces ceteris paribus demand by one text message (phone call). Moreover, we find significant weekday effects for text messaging with a minimum on Wednesday (−0.126) and peaks on weekends (0.352, 0.255) and holidays (0.201).[14] The opposite is suggested for phone calls with a peak on Fridays (0.130) and minima on weekends (−0.287, −0.471) and holidays (−0.150). Finally, we find a positive roaming effect for phone calls. Though it is fairly small considering the average time participants spend abroad, this raises demand by (0.162).[15]

More generally, the results of specification 2) in Table 2.1 and 2.2 highlight the importance of considering the network size in the demand for text messaging and phone calls, respectively. For text messaging we find that an increase in local network size by two people increases the quantity demand for text messages ceteris paribus by one per day. Moreover, we notice that the coefficient for incoming text messages decreases by around 20%, though the general interpretation remains. For phone calls we find an effect in local network size which is twice as high as for text messaging and also accounts for most of the variation which was previously attributed to incoming traffic and partly also other substitutes. So, the effect of substitutes becomes quite small as well for incoming traffic.

The impact of incoming traffic provides an interesting explanation for why the substitution from text messaging and phone calls is likely to have a different effect on their demand. As noted in the previous paragraph, we find a strong and significant effect of incoming traffic on text messaging demand but a small effect for phone calls. This suggests that incoming text messages are perceived as information complements which foster the exchange of more information. Thus, information from incoming text messages raises demand to exchange more information via text messages. In contrast, phone calls are perceived as information substitutes. As a consequence, having received a phone call makes a person less likely to exchange more information by calling others. Intuitively, this makes sense, as a phone call allows a bi-directional exchange of information while a text message is restricted to one direction. Thus, for example, questions or ideas which relate to newly exchanged information can be directly exchanged in one and the same call, while communications via text messages require to writing a new text message.

The one-directional exchange of information may also give an explanation for why reductions of text messaging usage has been so strong in some countries. As the usage of text messaging depends also strongly depends on incoming traffic, a decrease in usage inherits a negative multiplier effect. For text messaging networks

[14]For brevity, weekday effects are not reported in the regression results.

[15]This might be deflated, as users spend only a few time periods abroad. In the dataset this involves less than 10% of the observations with varying roaming durations.

this implies that a reduction of usage from some users also affects usage in the remaining network as they receive less incoming text messages. Interestingly, this starts to happen even before users actually begin leaving the network, which can further facilitate the decline of usage in that network. In contrast, for phone calls such a strong demand reduction is rather unlikely, as it is primarily driven by network size. Thus, a particular strong reduction will only happen when people actually leave the network, not already once usage has declined. As a result, relating these findings to the rise of OTT messengers, it is rather unlikely that the usage of mobile phone calls will face a similar fast demand reduction as is currently attributed to the text messaging market.

Findings from this work on the relationship between incoming and outgoing traffic of mobile telecommunication services also shed new light on the modelling of consumer utility in the theoretical telephony literature. Cambini and T. M. Valletti (2008) criticise that previous papers account only inadequately for utility from receiving calls when modelling consumer utility. While seminal works consider only that consumers gain utility from making calls (Armstrong 1998, Laffont et al. 1998a and Laffont et al. 1998b), proceeding papers also include consumer utility from receiving calls but do not account for possible interactions between them (e.g. J.-Y. Kim and Lim 2001, Jeon et al. 2004). These interactions may occur when information received via incoming calls raises or lowers the demand for further calls. Therefore, Cambini and T. M. Valletti (2008) propose a model which accounts for this possible interaction. Findings in the empirical literature (e.g. Basalisco 2012) seem to back that modelling this interaction between incoming and outgoing calls is important.

Indeed, the findings of this work suggest that this is only partially true for traditional mobile telecommunication services. While the incoming and outgoing traffic of text messaging depend positively on each other, incoming traffic for phone calls only has a slightly negative effect on outgoing phone calls which is also not significant across all specifications. This may indicate that omitting the interdependency between incoming and outgoing traffic, as theoretically modelled in e.g. J.-Y. Kim and Lim (2001) Jeon et al. (2004), is not inevitably a limitation of these studies.

2.4.2 Robustness Checks

In order to ensure the validity of the results we perform various robustness checks. As weak instruments may create a large estimation bias (Bound et al. 1995), we test our instruments to ensure their relevance. However, the instruments used in this estimation seem to be quite strong. In the first stage all instruments for the respective endogenous variables are significant (p-value = 0.0000) which is further supported by the F-statistic, which is clearly higher than 10.

Another threat to the validity of our instruments might be serial correlation. As we employ lags from the (endogenous) regressors X_{it} as instruments we assume for the error term u_{it} that $E[X_{it}u_{it}] \neq 0$ but $E[X_{it-1}u_{it}] = 0$. However, this is not valid in the case of serial correlation when $E[u_{it}u_{it-1}] \neq 0$ and thus $E[X_{it-1}u_{it}] \neq 0$. Inspection of the autocorrelation and partial autocorrelation functions suggests that the serial correlation of an MA(1) type is present. In line with Anderson and Hsiao (1981) we use instead lagged differences of order 3 as instruments. Though this induces only slight changes in the coefficients as becomes obvious in the comparison of specifications 2) and 3) for the respective estimations. Furthermore, as noted above the standard errors are still valid as these have been HAC corrected.

As the analysis is based on unbalanced panel data the results might be void to an estimation bias if entry or attrition occurs in a non-random fashion. We certainly have to assume that participants who make use of the *Device Analyzer* app are more likely to use their phone than the average mobile user. But this also implies that there is sufficient variation in the usage of various communication services. Furthermore, we can assume that the type of participants are fairly constant over time within the sample. If we expect the composition of subjects to change systematically within the sample over time then the results of the estimation should alter when adjusting the time period of the analysis. However, we ran our set of regressions for different time periods and find no change in the significance or interpretation of the regression results. We also find similar results when we test different specifications with monthly or annual time dummies.

2.5 Discussion

Initially, it may seem surprising that usage of OTT messengers complements the demand for text messaging services in Norway. However, it matches the patterns of field data which was observed in previous plots: Despite the rising popularity of OTT messengers, usage of traditional mobile telecommunication service has been fairly constant both on an aggregate level but also in the dataset (see Table 2.1, Table 2.4). This is complemented by scatterplots on average daily usage which do not suggest a negative relationship between traditional mobile telecommunication services and OTT messengers (see Table 2.4). Similarly, the average usage of both service types on an individual level are not asymmetric and indicate instead similar usage intensities for both services (see Table 2.5).

Indeed, a possible explanation for the complementary demand relationship between both services may be rooted in the composition of earnings in the Norwegian mobile market. These were in strong decline for text messaging and time-charged traffic after the peak of text messaging usage in 2009. In contrast, earnings from subscriptions and setup were steadily rising. This may suggest that the current market situation is the result of a timely shift of the industry from usage based pricing to subscription bundles. As such, the competitive price advantage of OTT messengers has vanished and the mobile industry has been able to keep not only customers but also earnings from another revenue sources. As most subscriptions include free text messages and phone calls, while OTT messengers are essentially free of charge, prices for these communication services are indifferent to consumers. As a consequence the advantage of OTT messengers over text messaging boils down to their extended functionality. Moreover, as both communication services are not compatible, users need to revert to text messaging when forward information to those users which exclusively use text messaging.[16] Given the high popularity of text messaging and the strong presence of network effects in the market this is often likely the case. Hence, this may explain the background of why demand for OTT messengers complements the demand for text messages and does not substitute it.

So how does the aforementioned market development relate to the research question of this paper: Do traditional mobile telecommunication services and OTT messengers form a joint market? Our results indicate that both services are demand complements and thus that demand for both markets is interrelated in Norway. However, we do not find any evidence that both services form a joint market from the perspective of competition policy. As such, the current regime for competition and regulation policy still applies and there is no evidence on similar markets to alter this. Though it is possible that the outlined development above is the outcome from competitive forces beforehand, it is not sufficient as evidence and it needs more research to evaluate it.

In further research it may also be interesting to study the future market development. Recent statistics report a drop in aggregate text messaging usage for the last two years in Norway. But, with a decline of 9% and 6%, respectively, this is still small compared to reductions of text messaging in other countries (Germany -41%, Italy -40%, and the UK -15.3% in 2015).[17] Additionally, absolute numbers

[16] The idea is analogous to the mechanism explained in Andersson et al. (2009) for the text messaging and mobile phone complementarity.

[17] Numbers for Norway based on own calculations, data: Norwegian Communication Authority (2018). For the other countries see Bundesnetzagentur (2015), Ofcom (2015), AGCOM (2015).

suggest that aggregate text messaging usage are still fairly common with more than 1,000 messages per capita in 2017, so the data employed for the analysis is still very current. Nonetheless, given the strongly rising popularity of OTT messengers, these results may differ for countries were reductions of text messaging where stronger and it may also be doubted whether a market tipping can be prevented in Norway for the future.

An interesting finding in the analysis is that industry earnings have been growing in the past, despite the rising popularity of OTT messengers. Though this paper cannot answer whether the shifting from pricing to the access level originates from a competitive response to OTT messengers, it can be noted that it reduces competition with OTT messengers at the access level, while the mobile industry profits from higher demands for data services as consumers increasingly use OTTs. Consequently, the rise of OTT messengers does not necessarily harm traffic and earnings in the mobile industry as observed in other countries. Certainly, this is not always the case and it needs to be distinguished between different types of mobile providers in the industry: Mobile virtual network operators (MVNO), who do not own any infrastructure themselves and create value by repacking and reselling mobile services in bundles, face a limited leeway in a market with unlimited bundles. Instead, mobile network operators (MNO) who own mobile networks themselves and use the data which is generated as a competitive advantage: Either they bundle their products with the most popular OTT-services themselves (see also Peitz and T. Valletti 2015, p. 910) or they sell their collected information on usage of OTT-services to other business. In any case it is of high importance that MNOs in particular adapt their business model to OTT messengers in timely fashion, otherwise this may also affect investments in the mobile network infrastructure. This affects not only the user experience of mobile services but also from OTTs. Consequently, it is important that competition and regulatory authorities monitor this market development closely and ensure that the mobile industry has not only have sufficient incentives to adapt but also that regulation gives sufficient leeway for investments in the mobile network infrastructure (Peitz and T. Valletti 2015, p. 911).

Finally, the topic of this paper also touches on the issues of interoperability and standards of OTT messengers. Incompatibility between different services may induce switching costs for consumers which reduce substitutions to other services and thus lower competition in the market (see also Klemperer 1995, p. 517). Though traditional mobile telecommunication services are offered by various firms, most countries and MNOs employ the common GSM standard. Thus mobile users are able to exchange communication with other mobile users independent of their provider.

Messages and contacts are stored locally on their device, so these can be kept when switching the provider. Number portability allows consumers in Europe but also in other countries to keep their mobile number when switching the provider.[18] However, this is different for OTT messengers, which are typically based on exclusive and proprietary standards. Hence, their users can neither exchange communication with users from other OTT messengers, nor can they transfer their user data.

The introduction of the GDPR is an important step towards raising competition between OTT messengers, as it grants users in the EU the right for data portability and thus lowers switching costs for consumers (European Union 2016b). Graef (2015) argues that this is not sufficient and that regulation should also include network interoperability to address the lock-in effects of consumers due to network externalities. But, given the huge heterogeneity of OTT messengers and the rapid technological development of OTT messengers it may queried whether a regulation can adequately address this question. Thus, further research is required to evaluate this and how this regulation would affect market outcomes.[19] More generally, it seems a paradox in this context that consumers voluntarily consider changing to another service with higher switching costs, despite the advances by consumer protection policy to lower switching costs for consumers. A policy implication from this might be that consumer protection should not only focus on enforcing consumer rights, but should also elucidate consumers on the benefits of their rights such that they value these in their decision-making.

2.6 Conclusion

This paper is, to the best of our knowledge, the first to provide an empirical analysis of the demand effect by OTT messengers on text messaging and phone calls. We make use of an innovative dataset which includes very detailed information on smartphone usage and consider a novel approach to address this question which is embedded in the complexity of two-sided markets. In particular, we employ 79,545 observations of 787 users from Norway which were collected by a personal analytics app – *Device Analyzer* – between 2013 and 2014.

To address the problem that OTT messengers typically lack prices for consumers we apply a new method which employs quantities instead of prices to measure the substitution between traditional mobile telecommunication services and OTT

[18]Number portability is part of the EU policy for a joint digital market (European Commission 2019).

[19]Indeed, Klemperer (1995) argue that standards should be mandated in those areas where technological change is unlikely (p. 2054).

messengers. Furthermore, we control for various demand shifters on an individual level, to isolate the causal effect of OTT messengers on daily demand for traditional mobile telecommunication services. Our findings suggest that social and messaging apps complement the demand for text messaging and mobile voice services. Consequently, both markets are interrelated but do not constitute a joint market from the perspective of competition policy in this setting. To ensure the validity of our results various robustness checks have been conducted and different specifications have been tested.

More generally, we identify the nature of mobile telecommunication services as a key element in order to explain why the reduction of text messaging has been so drastic in some countries. In contrast to mobile telephony, text messaging as a one-way-communication service is also largely driven by incoming traffic. So, it is already sensible to traffic reductions even before changes in network size take place. This does not apply to mobile telephony which makes it rather unlikely that this market will face a similar drastic demand reduction in the future as is currently happening in the text messaging market. This also provides a new perspective on the modelling of consumer utility in communication networks in the theoretical literature. In particular, our findings suggest that incoming and outgoing traffic of text messaging depend positively on each other, while this is not inevitably the case for phone calls. Thus, it is not a limitation of theoretical models if consumers gain utility from incoming and outgoing phone calls but if their demand does not depend on the interdependency between them.

This work has provided an analytical framework and estimated how OTT messengers affect demand for mobile telecommunication services in Norway. In further research the presented modelling approach can be applied to investigate competition between traditional mobile telecommunication services and OTT messengers. This includes research in other countries and time periods for which the decline of text messaging has been more extensive to get a more complete picture. Considering that the European telecommunication market is about to converge it is also of particular interest whether national markets in the EU have been similarly affected by OTT messengers or whether market singularities persist and why.

Further research may also focus on competition between OTT messengers. Access to these services is often provided free of charge to users while OTT messengers make use of this data to sell advertisements. Given the new introduction of data protection laws in the European Union these may be of interest: Do privacy concerns affect consumption of OTT messengers and induce consumers to substitute to other OTT messengers? Do consumers make use of their new right of data portability and does the failing interoperability of different OTT messengers hinder consumers to substitute between these services? Given the dominance of Facebook and its services have gained in the market for OTT messengers this topic becomes also increasingly relevant for competition policy.

Bibliography

Abbate, J. (2000). *Inventing the Internet*. MIT Press, Cambridge, Massachusetts.

AGCOM. (2015). Annual Report 2015. Retrieved February 27, 2017, from https://www.agcom.it/annual-report

Anderson, T. W., & Hsiao, C. (1981). Estimation of Dynamic Models with Error Components. *Journal of the American Statistical Association*, *76*(375), 598–606.

Andersson, K., Foros, Ø., & Steen, F. (2009). Text and voice: Complements, substitutes or both? *Industrial and Corporate Change*, *18*(6), 1231–1247.

Armstrong, M. (1998). Network Interconnection in Telecommunications. *The Economic Journal*, *108*(448), 545–564.

Armstrong, M. (2006). Competition in two-sided markets. *RAND Journal of Economics*, *37*(3), 668–691.

Barth, A.-K., & Heimeshoff, U. (2014a). Does the growth of mobile markets cause the demise of fixed networks? *Telecommunications Policy*, *38*(11), 945–960.

Barth, A.-K., & Heimeshoff, U. (2014b). What is the magnitude of fixed-mobile call substitution? *Telecommunications Policy*, *38*(8-9), 771–782.

Basalisco, B. (2012). The effect of user interaction on the demand for mobile text messages: Evidence from cross-country data. *Information Economics and Policy*, *24*(2), 132–144.

Berec. (2018). Termination rates at European level January 2018. Retrieved October 28, 2018, from https://berec.europa.eu/eng/document%5C_register/subject%5C_matter/berec/reports/8162-termination-rates-at-european-level-january-2018

Bound, J., Jaeger, D. A., & Baker, R. M. (1995). Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatory Variable is Weak. *Journal of the American Statistical Association*, *90*(430), 443–450.

Briglauer, W., Schwarz, A., & Zulehner, C. (2011). Is fixed-mobile substitution strong enough to de-regulate fixed voice telephony? evidence from the austrian markets. *Journal of Regulatory Economics*, *39*(1), 50–67.

Bundesnetzagentur. (2015). Jahresbericht 2014. Retrieved February 27, 2017, from https://www.bundesnetzagentur.de/DE/Allgemeines/Presse/Mediathek/Berichte/berichte-node.html

Cambini, C., & Valletti, T. M. (2008). Information Exchange and Competition in Communications Networks. *The Journal of Industrial Economics*, *56*(4), 707–728.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press, New York.

Caves, K. W. (2011). Quantifying price-driven wireless substitution in telephony. *Telecommunications Policy*, *35*(11), 984–998.

Dewenter, R., Heimeshoff, U., & Loew, F. (2017). Market Definition of Platform Markets. Retrieved October 24, 2018, from https://econpapers.repec.org/paper/risvhsuwp/2017_5f176.htm

European Commission. (1997). Commission notice on the definition of relevant market for the purposes of community competition law. *Official Journal of the European Communities*, *C372*(3), 5.

European Commission. (2019). The European Commissions Priority on the Digital Single Market. Retrieved March 15, 2019, from https://ec.europa.eu/commission/priorities/digital-single-market_en

European Union. (2002). Directive 2002/58/EC of the European Parliament and of the Council of 12 July 2002 concerning the processing of personal data and the protection of privacy in the electronic communications sector (Directive on privacy and electronic communications). *Official Journal L 201*, *L 201*.

European Union. (2016a). Commission Implementing Regulation (EU) 2016/2286 of 15 December 2016 laying down detailed rules on the application of fair use policy and on the methodology for assessing the sustainability of the abolition of retail roaming surcharges and on the application to be submitted by a roaming provider for the purposes of that assessment. *Official Journal of the European Union*, *L 344*.

European Union. (2016b). Regulation of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). *Official Journal of the European Union*, *L119*.

European Union. (2019). EPrivacy Directive. *Official Journal of the European Union*, *L 201*.

Evans, D. S., & Noel, M. D. (2008). The analysis of mergers that involve multisided platform businesses. *Journal of Competition Law & Economics*, *4*(3), 663–695.

Facebook. (2017). Facebook. Retrieved February 28, 2017, from https://investor.fb.com/home/default.aspx

Feasey, R. (2015). Confusion, denial and anger: The response of the telecommunications industry to the challenge of the Internet. *Telecommunications Policy*, *39*(6), 444–449.

Filistrucchi, L., Geradin, D., van Damme, E., & Affeldt, P. (2014). Market definition in two-sided markets: Theory and practice. *Journal of Competition Law & Economics*, *10*(2), 293–339.

Gerpott, T. J. (2015). Sms use intensity changes in the age of ubiquitous mobile internet access - a two-level investigation of residential mobile communications customers in germany. *Telematics and Informatics*, *32*(4), 809–822.

Gerpott, T. J., & Thomas, S. (2014). Empirical research on mobile Internet usage: A meta-analysis of the literature. *Telecommunications Policy*, *38*(3), 291–310.

Google. (2018). Data and file storage overview. Retrieved October 24, 2018, from https://developer.android.com/guide/topics/data/data-storage

Graef, I. (2015). Mandating portability and interoperability in online social networks: Regulatory and competition law issues in the European Union. *Telecommunications Policy*, *39*(6), 502–514.

Gruber, H. (2005). *The Economics of Mobile Telecommunications*. Cambridge University Press, New York.

Grzybowski, L. (2014). Fixed-to-mobile substitution in the european union. *Telecommunications Policy*, *38*(7), 601–612.

Grzybowski, L., & Liang, J. (2015). Estimating demand for fixed-mobile bundles and switching costs between tariffs. *Information Economics and Policy*, *33*, 1–10.

Grzybowski, L., & Pereira, P. (2008). The complementarity between calls and messages in mobile telephony. *Information Economics and Policy*, *20*(3), 279–287.

Grzybowski, L., & Verboven, F. (2016). Substitution between fixed-line and mobile access: The role of complementarities. *Journal of Regulatory Economics*, *49*(2), 113–151.

Holcombe, A. N. (1911). *Public Ownership of Telephones on the Continent of Europe*. Houghton Mifflin.

Jeon, D.-S., Laffont, J.-J., & Tirole, J. (2004). On the receiver pays principle. *The RAND Journal of Economics*, *35*(1), 85.

Katz, M. L., & Shapiro, C. (1985). Network Externalities, Competition, and Compatibility. *The American Economic Review*, *75*(3), 424–440.

Kim, J.-Y., & Lim, Y. (2001). An economic analysis of the receiver pays principle. *Information Economics and Policy*, *13*(2), 231–260.

Kim, Y., Telang, R., Vogt, W. B., & Krishnan, R. (2010). An empirical analysis of mobile voice service and SMS: A structural model. *Management Science*, *56*(2), 234–252.

Klemperer, P. (1995). Competition when consumers have switching costs: An overview with applications to industrial organization, macroeconomics, and international trade. *The Review of Economic Studies*, *62*(4), 515–539.

Laffont, J.-J., Rey, P., & Tirole, J. (1998a). Network Competition: I. Overview and Nondiscriminatory Pricing. *The RAND Journal of Economics*, *29*(1), 1–37.

Laffont, J.-J., Rey, P., & Tirole, J. (1998b). Network Competition: II. Price Discrimination. *The RAND Journal of Economics*, *29*(1), 38–56.

Lange, M. R., & Saric, A. (2016). Substitution between fixed, mobile, and voice over IP telephony – Evidence from the European Union. *Telecommunications Policy*, *40*(10-11), 1007–1019.

Norwegian Communication Authority. (2015). The Norwegian Electronic Communication Service Market 2014. Retrieved February 27, 2017, from https://eng.nkom.no/market/telecom-services/statistics/the-norwegian-ecom-market-reports

Norwegian Communication Authority. (2018). Ekomstatistikken. Retrieved October 27, 2018, from http://eng.nkom.no/market/telecom-services/statistics/the-norwegian-ecom-market-reports/_attachment/19519?_ts=14f8e70303a

Ofcom. (2015). The Communications Market Report 2015: United Kingdom. Retrieved February 27, 2017, from https://www.ofcom.org.uk/research-and-data/multi-sector-research/cmr/cmr15/uk

Oghuma, A. P., Chang, Y., Libaque-Saenz, C. F., Park, M.-C., & Rho, J. J. (2015). Benefit-confirmation model for post-adoption behavior of mobile instant messaging applications: A comparative analysis of KakaoTalk and Joyn in Korea. *Telecommunications Policy*, *39*(8), 658–677.

Peitz, M., & Valletti, T. (2015). Reassessing competition concerns in electronic communications markets. *Telecommunications Policy*, *39*(10), 896–912.

Rochet, J.-C., & Tirole, J. (2003). Platform Competition in Two-Sided Markets. *Journal of the European Economic Association*, *1*(4), 990–1029.

Scaglione, M., Giovannetti, E., & Hamoudia, M. (2015). The diffusion of mobile social networking: Exploring adoption externalities in four G7 countries. *International Journal of Forecasting*, *31*(4), 1159–1170.

Stork, C., Esselaar, S., & Chair, C. (2017). OTT - Threat or opportunity for African Telcos? *Telecommunications Policy*, *41*(7), 600–616.

U.S. Department of Justice and the Federal Trade Commission. (2010). Horizontal Merger Guidelines. Retrieved February 27, 2017, from https://www.ftc.gov/sites/default/files/attachments/merger-review/100819hmg.pdf

Vogelsang, I. (2010). The relationship between mobile and fixed-line communications: A survey. *Information Economics and Policy*, *22*(1), 4–17.

Wagner, D., Rice, A., & Beresford, A. (2013). Device Analyzer: Understanding Smartphone Usage. *10th International Conference on Mobile and Ubiquitous Systems: Computing, Networking, and Services, Tokyo, Japan*, 195–208.

Wagner, D. T., Rice, A., & Beresford, A. R. (2014). Device Analyzer: Large-scale mobile data collection. *ACM SIGMETRICS Performance Evaluation Review*, *41*(4), 53–56.

Web Archive. (2017). WhatsApp Messenger - Android-apper på Google Play. Retrieved March 25, 2017, from https://web.archive.org/web/20141231031655/https://play.google.com/store/apps/details?id=com.whatsapp%5C&hl=no

2.7 Appendix

Variable	Description
Q^{out}_{kit}	quantity of outgoing text messages or phone calls
Q^{in}_{kit}	quantity of incoming text messages or phone calls
I_{kit}	average length of text messages in characters or duration of phone calls in seconds
$Q_{phone\,calls}$	quantity of phone call usage, defined as incoming and outgoing phone calls
$Q_{text\,messaging}$	quantity of text messaging usage, defined as incoming and outgoing text messages
$Q_{messenger\,apps}$	quantity of messaging app usage, measured by how often an app of the category *messenger* has been in foreground while the screen is on
$Q_{social\,apps}$	quantity of social app usage, measured by how often an app of the category *social* has been in foreground while the screen is on.
N_{kit}	local network size of traditional mobile telecommunication services, measured by the number of people contacted via text messaging or phone calls.
R_{it}	roaming status, measured by a periodical check if this status is positive.

Table 2.3: *Definition of Used Variables*

Statistic	N	Mean	St. Dev.	Min	Max
$Q^{out}_{textmessaging}$	79,545	3.9	5.6	0	40
$Q^{in}_{textmessaging}$	79,545	5.3	7.1	0	50
$N_{textmessaging}$	79,545	3.2	2.4	0	12
$I_{textmessaging}$	79,545	51.4	41.4	0	863
$Q^{out}_{phonecalls}$	79,545	2.7	3.8	0	25
$Q^{in}_{phonecalls}$	79,545	2.4	3.0	0	24
$N_{phonecalls}$	79,545	3.6	3.1	0	22
$I_{phonecalls}$	79,545	385.6	1,108.7	0	42,140
$Q_{textmessaging}$	79,545	9.0	11.6	0	90
$Q_{phonecalls}$	79,545	5.0	6.0	0	48
$Q_{messenger}$	79,545	2.3	5.2	0	49
Q_{social}	79,545	6.2	8.9	0	66
R	79,545	2.4	11.8	0	126

Table 2.4: *Summary Statistics*

	$Q^{out}_{textmessaging}$	$Q^{in}_{textmessaging}$	$N_{textmessaging}$	$I_{textmessaging}$	$Q_{phonecalls}$	$Q_{messenger}$	Q_{social}
$Q^{in}_{textmessaging}$	0.69***						
$N_{textmessaging}$	0.60***	0.64***					
$I_{textmessaging}$	0.09***	0.22***	0.35***				
$Q_{phonecalls}$	0.28***	0.26***	0.45***	0.14***			
$Q_{messenger}$	0.19***	0.11***	0.13***	0.03***	0.10***		
Q_{social}	0.19***	0.14***	0.16***	0.07***	0.11***	0.30***	
Q_R	0.01***	0.03***	0.02***	0.04***	0.01*	-0.01***	-0.03***

	$Q^{in}_{phonecalls}$	$Q^{out}_{phonecalls}$	$N_{phonecalls}$	$I_{phonecalls}$	$Q_{textmessaging}$	$Q_{messenger}$	Q_{social}
$Q^{out}_{phonecalls}$	0.55***						
$N_{phonecalls}$	0.74***	0.75***					
$I_{phonecalls}$	0.17***	0.40***	0.30***				
$Q_{textmessaging}$	0.26***	0.27***	0.32***	0.10***			
$Q_{messenger}$	0.09***	0.09***	0.10***	0.03***	0.15***		
Q_{social}	0.11***	0.09***	0.12***	0.03***	0.17***	0.30***	
R	0.02***	0.00	-0.01*	-0.01***	0.03***	-0.01***	-0.03***

Table 2.5: *Correlation Matrix for Text Messaging and Phone Calls*

instrument variable	F-Statistic, significance level
$Q^{in}_{phone\,calls}$	6,034.556***
$Q_{text\,messaging}$	6,582.101***
$Q_{messenger}$	4,910.415***
Q_{social}	4,856.321***

*p<0.1; **p<0.05; ***p<0.01, HAC robust standard errors.

Table 2.6: *First Stage Results of the Instrumental Variables in the Text Messaging Regression*

instrument variable	F-Statistic, significance level
$Q^{in}_{text,messaging}$	6,498.039***
$Q_{phonecalls}$	5,708.720***
$Q_{messenger}$	4,910.147***
Q_{social}	4,856.167***

*p<0.1; **p<0.05; ***p<0.01, HAC robust standard errors.

Table 2.7: *First Stage Results of the Instrumental Variables in the Voice Call Regression*

Chapter 3

What Would Households Pay for a Reduction of Automobile Traffic? Evidence From Nine German Cities

Co-authored with Daniel Czarnowske

3.1 Introduction

The past century can be seen as the golden age for automobiles. By offering consumers the option to travel anywhere, any time, automobiles quickly became not only a symbol of freedom but also a status symbol in society (Gartman 2004). Today, the automobile is a mass produced product. In Europe an average of five out of 10 persons own an automobile (Eurostat 2019) while in the US around eight out of 10 people are automobile owners (Davis and Boundy 2019). However, traveling by car is not only convenient, it is also important for economic reasons. For example, 86% of the US workforce use their automobile to commute to work (United States Census Bureau 2017). The popularity of automobiles is also reflected in the infrastructure of many cities in the US and Europe, which are adapted to the needs of automobile drivers: On streets, typically a major share of the lanes is dedicated to automobiles, while only a minor share of the space is allocated to pedestrians and cyclists. The timing of traffic signals is optimized for a continuous flow of automobiles, also known as the 'green wave.' In Germany construction law contributes to a continuous growth of parking lots, by regulating the minimum number of parking lots for residential buildings and other facilities (e.g., LBO Baden Württemberg 2019).

Over the course of time the positive image of automobiles has faded and automobiles are looked at more critically in society. Their emissions are known to cause significant harm to human health but also to the environment. This includes air pollution like particulate matter, nitrogen dioxide, carbon dioxide, black smoke, benzene, ozone, polycyclic aromatic hydrocarbons or lead. Evidence suggests that air pollution raises the risk of cardiopulmonary causes, heart attacks, cancer, allergies, asthma attacks (WHO 2005, p. 125, 126), and infant mortality (Knittel et al. 2016), and also lowers cognitive performance (Shehab and Pope 2019). For example, in the US, the UK, and Germany emissions from land traffic account for around 20% of the mortality by ambient particulate matter and ozones.[1] Carbon dioxide emissions from automobiles contribute to global warming and climate change (Houghton 1996). In the EU 21% of total carbon dioxide emissions originate from automobiles (Commission 2019b). Estimates suggest that damages from climate change will amount to at least €190 billion in the EU if no further actions are taken (Carlos et al. 2014). Finally, noise emissions are not only found to increase the occurrence of stress and depression but they also lower well-being in general (Gee and Takeuchi 2004).

Besides air pollution, automobile traffic is associated with various effects which harm public health. Road crashes kill 94,500 people in high income countries every

[1]Number refers to particular matter smaller than 2.5 micrometers.

year.[2] Approximately 50% of these crashes affect vulnerable road users like cyclists or pedestrians. For children and young people road crashes are particularly an issue, as this is the leading cause of death of those aged between five to 29 (WHO 2018). Delays by traffic jams are not only costly (EU: nearly € 100 billion annually), there is also evidence that extreme congestions may increase domestic violence (Beland and Brent 2018). Using an automobile instead of other more active transportation alternatives bears significant opportunity costs as it raises obesity. In the OECD, overweight and related diseases reduce the GDP, on average, by 3,3%, cost 92 million lives, and will lower life expectancy by nearly three years by 2050 (OECD 2019).

To reduce damages to health and the environment from automobiles in Europe, different regulations have been put in place in Europe. This includes taxes on CO2-based motor vehicles, gasoline, and various restrictions to reduce inner-city traffic at the local level. For example, various metropolis like London, Oslo, Stockholm or Mailand, which have been naturally plagued by excessive traffic, have introduced congestion prices. These prices typically range between €5 and €10 per day and are usually differentiated by criteria such as vehicle size, time or engine type (Urban Access Regulation 2019). With the EU directive for clean air, air pollution has become a much discussed topic also beyond the metropolis. This EU directive aims to reduce air pollution by 2020 below the threshold where it significantly affects human health and the environment. Today, 227 cities in seven European countries have created low emission zones to restrict access to cities for automobiles above a certain emission threshold.[3] In Italy, 306 cities have restricted traffic in various districts to residents only. Other regulations include the ban of lorries in the city or prohibited access for all automobiles (Urban Access Regulation 2019).

However, despite the measures taken by various cities a number of countries in the EU have failed to comply with the EU directive for clean air. As a consequence, the European Commission has taken these countries to the EU court of justice (Commission 2019a, Commission 2018). Among those countries which have violated the EU directive for clean air is Germany. Despite an emergency program[4] by the German government, 57 cities exceeded the critical value for nitrogen oxide in 2018 (Umweltbundesamt 2019).

The aforementioned damages can be considered as externalities from automobile traffic and thus it is important to address these in regulation policy. Since their actual

[2]Countries are classified as high-income countries in this study if their gross national income per capita exceeds US $12,235.

[3]Namely these countries are: Germany, Italy, Netherlands, Belgium, Denmark, Norway and the UK.

[4]Among others, this program includes subsidies for cars and electric bikes and the expansion of cycle networks.

costs from consumption are not incorporated in prices for consumers, there will be excess consumption absent regulation. However, addressing this topic appropriately in regulation policy is a challenging task as it is closely linked to questions of social justice. Ignoring the social implications of environmental policies can lead to a strong public backlash, as recently observed in France. As part of its environmental policy to reach carbon neutrality by 2050, the French government had planned to raise fuel taxes in 2018 by €7.6 cents per litre diesel and €3.9 cents per litre petrol (Republique Français 2018 Republique Français 2017). However, given that fuel prices at that time period were already on a high level, this lead to protests by more than 280,000 people and gave rise to the 'yellow-vest' protest movement. In consequence, the French government had to postpone the increase of fuel taxes and promised various tax reliefs worth more than €10 billion in order to tame the tensions (Economist 2019, Economist 2018).

This paper estimates the marginal and non-marginal willingness to pay for a reduction of traffic. Using a novel estimation approach and a very detailed dataset, it contributes to the political debate by indicating to what extend consumers value political efforts for traffic reductions. In detail, we make use of 533,402 observations which were collected between October 2016 and December 2019 in nine German cities and match these with data from Openstreetmap on street characteristics. For the estimation, we use a novel approach by Bishop and Timmins (2019) which allows us to determine the marginal and non-marginal willingness to pay without instrumental variables and their associated estimation biases, while making use of only moderate econometric assumptions. In our analysis we are able to control for a number of apartment characteristics as well as various location-specific variables. Specifically, we consider for each apartment the minimum distance to various shops, amenities and to the city center.

Our findings suggest that, after controlling for rich apartment characteristics, traffic from automobiles significantly affects apartment prices in cities and that consumers have a positive willingness to pay to reduce traffic from automobiles. We estimate that the non-marginal willingness to pay for a reduction of traffic per household and year ranges by city between €30.3–59.2 for a 10% reduction, €93.8–158.3 for a 20% reduction, and €190.6–252€ for a 30% reduction. The highest non-marginal willingness to pay for a reduction of traffic is observed in Frankfurt am Main, the lowest in Leipzig. Moreover, we compute the expected gains for a reduction of traffic at the city level. In addition to the non-marginal willingness to pay for a reduction of traffic, this considers for the composition of the road network as well as for the number of households. Accordingly, these expected gains amount between €163,970–1,019,454 for a 10% reduction, €484,023–3,261,837 for a 20% reduction and €1,018,240–6,727,148 for a 30% reduction. The highest expected gains for a reduction of traffic is observed in Munich, the lowest in Leipzig. This is also relevant for the current debate of regulation is able to meet the environmental goals which are currently discussed.

The remainder of the paper is organized as follows: Section 2 introduces our econometric model, describes the necessary assumptions which have been made and the estimation procedure. Section 3 gives an overview of our data set and provides various descriptive statistics of the variables which are used in the further analysis. Section 4 presents our estimates for the marginal and non-marginal willingness to pay as well as the expected gains for exemplary traffic reductions. Section 5 discusses the allocative and distributive effects of a policy intervention. Section 6 concludes.

3.2 Econometric Model

Estimating the willingness to pay to reduce traffic is not straightforward, as traffic is not a good which is publicly traded in the market. One opportunity to address this issue are hedonic price models which determine the implicit price of a product based on product characteristics. Compared to other valuation methods hedonic price models have several advantages as their analysis is typically based on observed rather than stated preferences. First, this means that data is gathered from actual consumption decisions as observed in the market and not a hypothetical setting (e.g., in surveys). Second, it allows us to study the consumption decision in the context of other variables, which typically confound the decision making e.g. apartment characteristics. Third, the number of observations can be easily scaled in the analysis, while this can become fairly costly in surveys (Baranzini et al. 2008, p. 4).

Rosen (1974) proposed a structural framework for hedonic price models to estimate the marginal willingness to pay of consumers for a differentiated good.[5] His approach consists of a two-step procedure in which the price of a good is first regressed on its characteristics. Then the marginal price of the characteristic of interest is computed for each unit of observation and then regressed against a set of supply and demand shifters, respectively, to infer the marginal willingness to pay. A particular strength of the model is that it allows us to compute the effect of a non-marginal policy change on consumers' marginal willingness to pay (Bishop and Timmins 2019).

A well-known drawback of the approach from Rosen (1974) is that the estimation

[5]Previous work on hedonic price models has been done, for example, by Lancaster (1966) or Griliches (1961).

gives rise to multiple endogeneity problems. One source may originate from the classical endogeneity problem in markets: The marginal hedonic price for a product characteristic is determined by the interaction of supply and demand. Bartik (1987) and Epple (1987) stress another source of endogeneity which may arise from the non-linear hedonic price function. This allows consumers to endogenously choose the prices and quantities of a characteristic. In consequence, the choice of both price and quantity of a product characteristic is influenced by unobserved taste preferences. For example, consumers with a higher preference for a specific characteristic will also consume more of it. Different suggestions have been made to address the endogeneity problems in Rosen's model with instrumental variables. But given that the variables of interests are determined in an equilibrium model, it is far from trivial to find valid instruments.

For example Kahn and Lang (1988) suggest exploiting variations in the distribution of firms and consumers between markets as these are likely to be independent of supply and demand equations. Though this does not only require homogeneity of preferences across markets, it is also questionable whether the variation between markets affects the endogenous variable sufficiently (Bishop and Timmins 2019). Eventually, this boils down to a common issue with instrumental variables: their application is widespread in the econometric literature, but their choice and the analysis based on them are typically subject to intensive debate.

For the analysis, this paper makes use of a new approach by Bishop and Timmins (2019) to determine the marginal and non-marginal willingness to pay in a likelihood estimation. Their work entails several benefits for the further analysis. First, it requires no instrumental variables. Second, the data requirements are fairly modest, as it requires no information on income or other such demographic information of households to estimate the marginal and non-marginal willingness to pay. Third, the framework relies only on fairly modest econometric assumptions. Fourth, the approach is computationally simple and straightforward.

Following Bishop and Timmins (2019) and adapting their framework to our setting we observe $i = 1, \ldots, N$ households in $j = 1, \ldots, J$ markets. For the moment assume that each city is considered as a separate market. Household i in market j pays a monthly rental price for its apartment which is determined by the following function:

$$p = p(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}) \tag{3.1}$$

where z_{ij} denotes the amenity of interest, $\mathbf{x}_{ij}$ are additional control characteristics which might be either apartment or neighborhood-specific, while ξ_{ij} refers to other unobserved apartment characteristics. Further, we assume that the utility function of household i in market j is defined as follows:

$$u = u(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}, c_{ij}, \nu_{ij}) \tag{3.2}$$

and depends on the amenities (z_{ij}, $\mathbf{x}_{ij}$), a numeraire consumption c_{ij}, unobserved household attributes ν_{ij}, and household income y_{ij}. Assuming that household i in market j maximizes utility, subject to its budget constraint, and normalizing the price of numeraire consumption to one allows us to rewrite the household's problem as

$$\begin{aligned} &\max_{i,j} \; u_j(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}, c_{ij}, \nu_{ij}) \\ &\text{subject to} \quad p(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}) + c_{ij} \leq y_{ij}\,. \end{aligned} \tag{3.3}$$

Under the assumption that the household's optimum lies on the budget line, we can reformulate utility as

$$u = u(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}, y_{ij} - p(z_{ij}, \mathbf{x}_{ij}, \xi_{ij}), \nu_{ij})\,. \tag{3.4}$$

Assuming quasi-linear utility in y_{ij} allows us to relax the data requirements so that we are able to estimate the parameters of the marginal willingness to pay function without household-specific income information. Following Bishop and Timmins (2019) we specify a quadratic utility function:

$$u = \alpha_{1j} z_{ij} + \frac{1}{2}\alpha_2 z_{ij}^2 + \nu_{ij} z_{ij} + g_j(\mathbf{x}_{ij}, \xi_{ij}) + y_{ij} - p_j(z_{ij}, \mathbf{x}_{ij}, \xi_{ij})\,, \tag{3.5}$$

which yields the following household optimal consumption of z_{ij}:

$$p'(z_{ij}) = \alpha_{1j} + \alpha_2 z_{ij} + \nu_{ij}\,, \tag{3.6}$$

where $p'(z_{ij}) = \partial p_j(z_{ij}, \mathbf{x}_{ij}, \xi_{ij})/\partial z_{ij}$, α_{1j} is a market-specific intercept, and α_2 is the slope of the marginal willingness to pay function.

Obviously, we are not able to fully isolate z_{ij} on the left-hand side of (3.6) without restricting the functional form of $p'(z_{ij})$. However, there is usually no theoretical justification for arbitrary parametric assumptions about the functional form. The traditional approach of Rosen (1974) leaves $p'(z_{ij})$ unrestricted and uses a two-step approach, where $p'(z_{ij})$ in (3.6) is replaced by an estimate from the hedonic regression (Bishop and Timmins 2019). It is well known that this approach leads to an endogeneity problem, so it is common practice to use instrumental variables for z_{ij}. Instead, Bishop and Timmins (2019) suggest an alternative approach where they first isolate ν_{ij} on the left-hand side:

$$\nu_{ij} = p'(z_{ij}) - \alpha_{1j} - \alpha_2 z_{ij} \, . \tag{3.7}$$

Under the assumption that ν_{ij} is normally distributed with variance σ^2_ν, they employ a change of variables such that the parameters $(\boldsymbol{\alpha}_1, \alpha_2, \sigma_\nu)$ can be estimated by maximum likelihood.[6] The corresponding log-likelihood function is

$$L\left(\boldsymbol{\alpha}_1, \alpha_2, \sigma_\nu\right) = \sum_{i=1}^{N}\sum_{j=1}^{J} \log\left(\sigma_\nu \phi\left(\hat{\nu}_{ij}(\boldsymbol{\alpha}_1, \alpha_2)\right) \widehat{J}(\alpha_2)\right) \, , \tag{3.8}$$

where $\phi(\cdot)$ is the probability density function of the standard normal distribution, $\hat{\nu}(\boldsymbol{\alpha}_1, \alpha_2)$ is (3.7) with $p'(z_{ij})$ replaced by an estimate from the hedonic regression, $\widehat{J}(\alpha_2) = |\hat{p}''(z_{ij}) - \alpha_2|$ is the Jacobian that stems from the application of the change of variables, and $\hat{p}''(z_{ij}) = \partial^2 \hat{p}_j(z_{ij}, \mathbf{x}_{ij}, \xi_{ij})/\partial z^2_{ij}$. Instead of maximizing (3.8) directly, Bishop and Timmins (2019) suggest using the following profile log-likelihood function:

$$\mathcal{L}\left(\alpha_2\right) = \sum_{i=1}^{N}\sum_{j=1}^{J} \log\left(\tilde{\sigma}_\nu(\alpha_2) \phi\left(\tilde{\nu}_{ij}(\alpha_2)\right) \widehat{J}(\alpha_2)\right) \, , \tag{3.9}$$

where $\tilde{\nu}_{ij}(\alpha_2)$ are the residuals of a regression of $\hat{p}'(z_{ij}) - \alpha_2 z_{ij}$ on market identifiers and $\tilde{\sigma}_\nu(\alpha_2) = \frac{1}{NJ}\sum_{i=1}^{N}\sum_{j=1}^{J} \tilde{\nu}_{ij}(\alpha_2)$. Thus, $(\boldsymbol{\alpha}_1, \alpha_2, \sigma_\nu)$ can be estimated from a simple univariate optimization problem. The corresponding standard errors can be obtained by a non-parametric bootstrap.[7]

Further, Bishop and Timmins (2019) show that their suggested approach is able to identify the parameters of the marginal willingness to pay function. More precisely, $\boldsymbol{\alpha}_1$ is identified from the average consumption of z_{ij}, σ_ν is identified from the variance of z_{ij}, and α_2 is identified from the nonlinearity of $p'(z_{ij})$. Intuitively, the nonlinearity of $p'(z_{ij})$ leads to differences in the level of consumption for different types of households, where the extent of these differences influences α_2. The availability of data on multiple markets provides additional sources of identification. For instance, the variation of z_{ij} and $p'(z_{ij})$ across markets (for a detailed treatment on different sources of identification see Bishop and Timmins 2019, section 2.2).

[6] Note that the distributional assumption about the true unobserved household attributes ν^0_{ij} is not overly restrictive. If it does not hold, the estimator simply becomes a pseudo-maximum likelihood estimator and is still consistent (See Greene (2012) chapter 14.8). Alternatively, the authors propose a generalized method of moments estimator that can be used to estimate the parameters of (3.6) and σ_ν.

[7] Alternatively, we could estimate the parameters of the hedonic price function and (3.6) simultaneously.

3.3 Data

A particular strength of this paper is that we unite detailed information on rental apartments with various location-specific variables. In total, our analysis is based on 533,402 observations from the seven largest cities in Germany (Berlin, Hamburg, Munich, Frankfurt, Düsseldorf, Cologne, Stuttgart) and the two major cities in eastern Germany (Leipzig and Dresden). We focus the analysis on the largest cities in Germany as excessive traffic and related externalities such as air pollution and noise are a particular issue there. We also consider two cities from eastern Germany, as even today, 30 years after the German reunification, various differences in the social and economic development can still be observed between East and West Germany (BMWi 2019). Against this background it will be interesting to see whether these differences can also be observed for the willingness to pay to reduce automobile traffic.

Data on the real estate market is scraped daily from the two major real estate portals for apartment rentals in Germany and was collected between October 2016 and December 2019. The data include very detailed information on prices, characteristics, and features of the apartment as well as the exact geographic coordinates.[8] For the analysis, we assume that the posted rental price for the apartment, exclusive of heating and other additional costs, corresponds to the actual rent paid by the tenant for the apartment. Given the high demand for rental apartments in German cities, this does not seem to be a strong assumption. For one, housing prices in the seven largest cities in Germany nearly doubled between 2010 and 2018 (Bundesbank 2019). For another, the duration of an advertisement in our data set is, with a median of 12 days, fairly short. Thus, it is unlikely that posted prices for apartments are renegotiated afterwards with the landlord. Finally, given that we consider a period of three years and three months in the analysis, we deflate the apartment prices with the consumer price index for rental housing at the state level.

Given that the willingness to pay for traffic reductions is determined from rental prices in the real estate market, one important consideration is their regulation. Principally, the regulation of rental prices may distort the willingness to pay as it potentially limits rents to a lower bound than in a unregulated market. This may distort the consumption decisions of consumers and lead to a misallocation in the market (Glaeser and Luttmer 2003). Thus it may also potentially bias the estimation of the willingness to pay.

[8]This is not possible for apartments where the postal code is the only geographic information. Thus, these apartments are excluded from the analysis, as it remains unknown how their rental price is affected by location-specific confounders.

Rent prices in Germany are regulated, but we argue that this regulation does not interfere with the analysis of this paper. First, the regulation of rental prices is not that restrictive with regard to the magnitude. Every three years it allows an increases in rental prices of up 20%. In cities, where housing prices have been particular excessive, these still amount to 15% within three years. In our data set rental price increases are restricted to 20% in Leipzig and 15% in Berlin, Hamburg, Munich, Frankfurt am Main, Düsseldorf, Cologne, Stuttgart, and Dresden (Haufe 2019). Second, the regulation of rental prices is also less restrictive as it is based on relative increases. Thus, prices can still be adjusted in accordance with the overall development of the market. This is a significant difference to a regulation which would enforce an absolute limit of rental prices. Third, there are important exceptions. Rental controls do not apply to newly built apartments or significantly refurbished apartments. Further, if the previous tenant has profited from refurbishment but was not charged a higher rental price, the landlord may increase the rental price for the next tenant beyond the restrictions of the rental control (§ 556e, BGB). Third, the rent regulation is not enforced by the state. Instead, the tenant has the right to request information on the previous rent from the landlord and then has to prove that the rent is excessive (§ 556g, BGB). Finally, and most importantly, the overall trend in rental prices is fairly constant and is seen to be upward sloping constant between 2010 and 2018, despite the introduction of rental price controls in 2013 and a further extension in 2015 (See for example (Bundesbank 2019). Thus, it is also not surprising that a study confirms that these regulations of rental prices have only a minor impact on the future rental income of investors (Kholodilin et al. 2016).

Data on the geolocations of various kinds of shops and amenities (e.g., cafés, bars, restaurants, supermarkets, banks, doctors) as well as street characteristics (speed, lanes) is gathered from Openstreetmap. Based on the latter information we also calculate for each street the mean capacity of automobiles per hour. To be more precise, we calculate for each street s in city c a physical upper bound for automobile traffic per hour:

$$\mathsf{traffic}_{\mathsf{cs}} = \frac{\mathsf{speed}_{\mathsf{cs}} \times \mathsf{lanes}_{\mathsf{cs}}}{\mathsf{automobile} + \mathsf{buffer}} \tag{3.10}$$

where we assume that the maximum capacity of a street s depends on the product of the maximum speed (in k.p.h) and the number of lanes, which is then divided by the average length of an automobile in Germany and a safety margin of one meter. We interpret this quantity as an indicator for potential traffic. For instance, if a household visits an apartment, it only has limited information about the true traffic per hour on the street of this apartment. However, this household can form some expectations about the potential traffic based on the number of lanes and the maximum speed. Afterwards, we match this quantity with the respective apartments which are located on that street. Apart from that, we compute for each apartment individually various linear distance measures to points of interest. For one, this includes the distance to the city center. For the analysis we assume that this corresponds to the location of the town hall, as cities in Germany are historically expanded around this center. For another, we calculate for each apartment the minimum distance to various groups of shops, amenities, public services, the next stop position for public transport, and to the next motorway junction.[9]

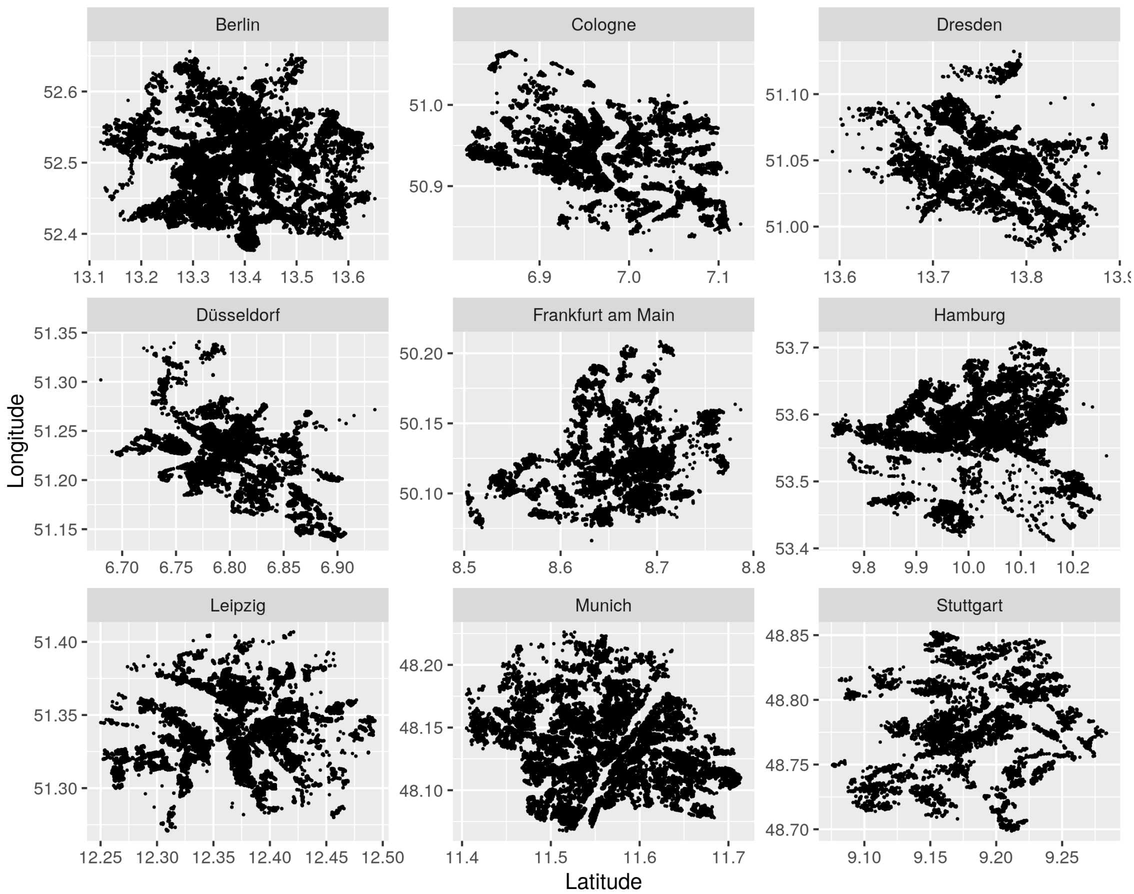

Figure 3.1: *Location of Apartments in Our Dataset by City. Own illustration. Data: Own data set*

Figure 3.1 displays with black dots the location of the apartments in our data set by city. It can be seen that our samples are fairly representative, as the apartments in our data set are equally distributed across cities and match the general outline of the respective cities fairly well. Remaining inner-city blank spaces can be typically explained with waterways (e.g., the river Elbe in Hamburg) or green areas (e.g., the

[9]For details see also Figure 4.

forest Dresdner Heide in Dresden).

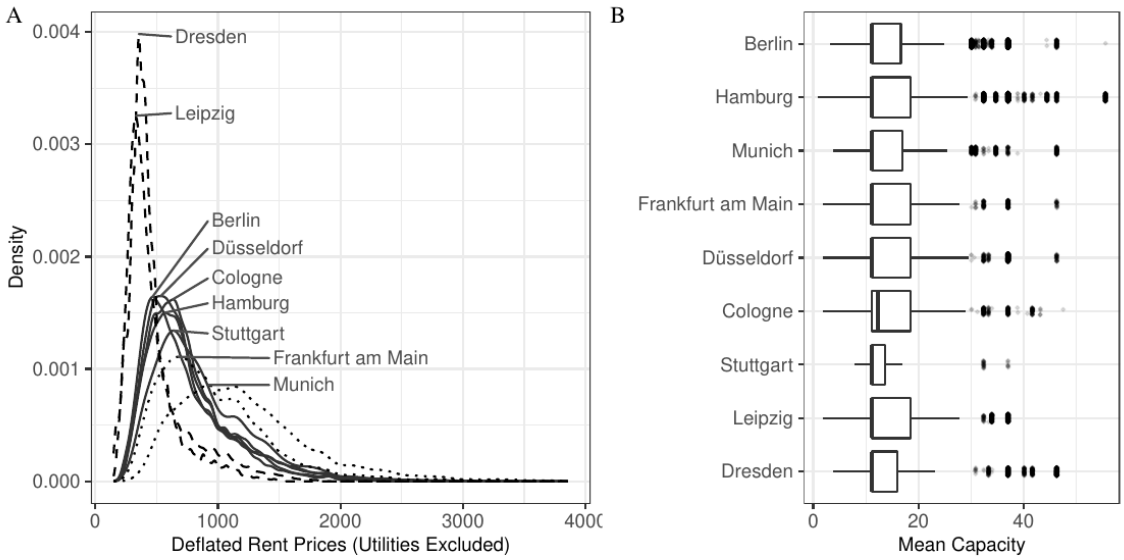

Figure 3.2: *Distribution of Rent Prices and Traffic in Different German Cities. Own illustration. Data: Own data set*

The main variables, which are used in our econometric model, are shown in Figure 3.2. The distribution of deflated rent prices differs significantly across cities in our data set. In Berlin, Düsseldorf, Cologne, Hamburg, Stuttgart, and Frankfurt am Main rent prices are centered around modes between €468 and €678. In contrast, the rent price distribution in Munich is much more platykurtic and is centered around a mode of €1,136 per month. This indicates that excess demand for apartments is much higher in Munich. At the same time the opposite is true for Dresden and Leipzig where the distribution of rent prices is much more leptokurtic and centered around a mode of €331 and €354 respectively. However, these price differences have been not put in context with apartment characteristics, which may also vary by city.

The variation of street capacity is fairly similar in Hamburg, Munich, Frankfurt, Düsseldorf, Cologne and Leipzig. This includes both the total distribution and the distribution of street traffic between the 25th and 75th percentile. A similar distribution can be observed for both Berlin and Dresden, though at a lower magnitude. A notable exception is the distribution of street capacity in Stuttgart, as the variation is much smaller and fewer outliers can be observed here. Among those cities considered for the analysis, Stuttgart is among the smallest cities. At the same time, the distribution of rent prices in Stuttgart indicates a notable shortage in apartment supply. Given that we match the apartments with the street in front of their house, it is not too surprising that fewer listings also imply less variation in street characteristics.

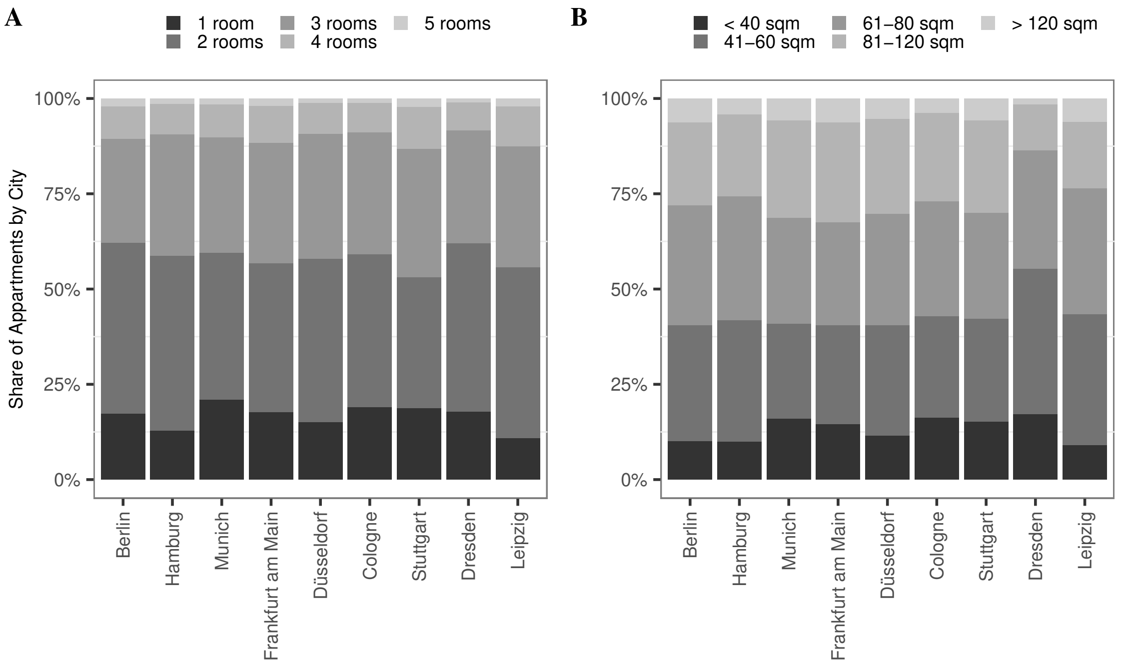

Figure 3.3: *Distribution of the Number of Rooms and Apartment Sizes. Own illustration. Data: Own data set*

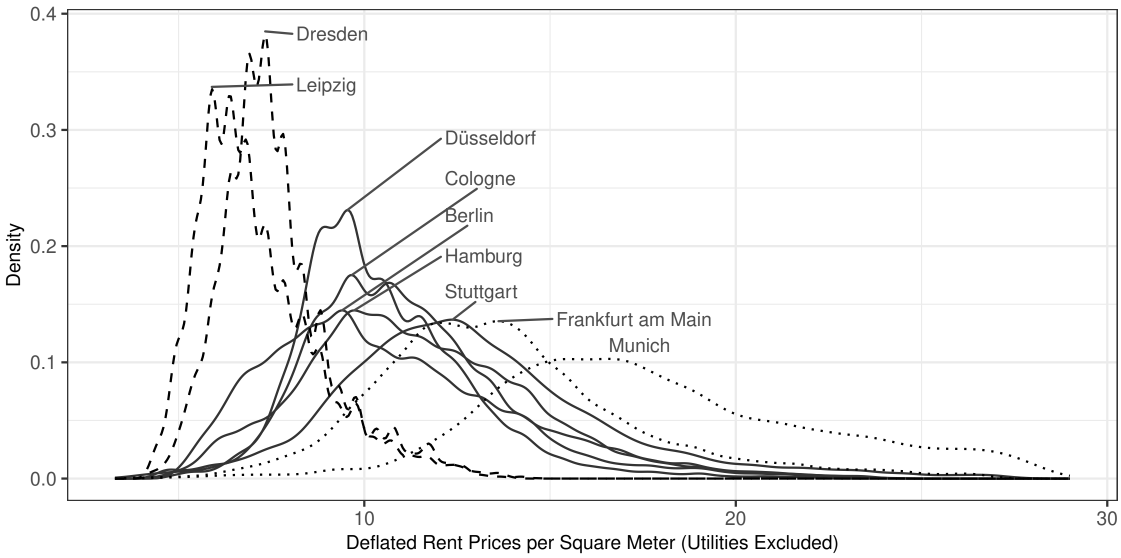

Figure 3.4: *Distribution of Rent Prices per Square Meter in Different German Cities. Own illustration. Data: Own data set*

Figure 3.3 displays the size of the apartments in our data set. It can be observed in plots A and B that the number of rooms as well as the size of the apartments varies significantly between different cities. In particular the share of apartments with either one-room or apartments that are under 40 sqm is substantially higher in Munich. This corresponds to the former observation that the price level for apartments in

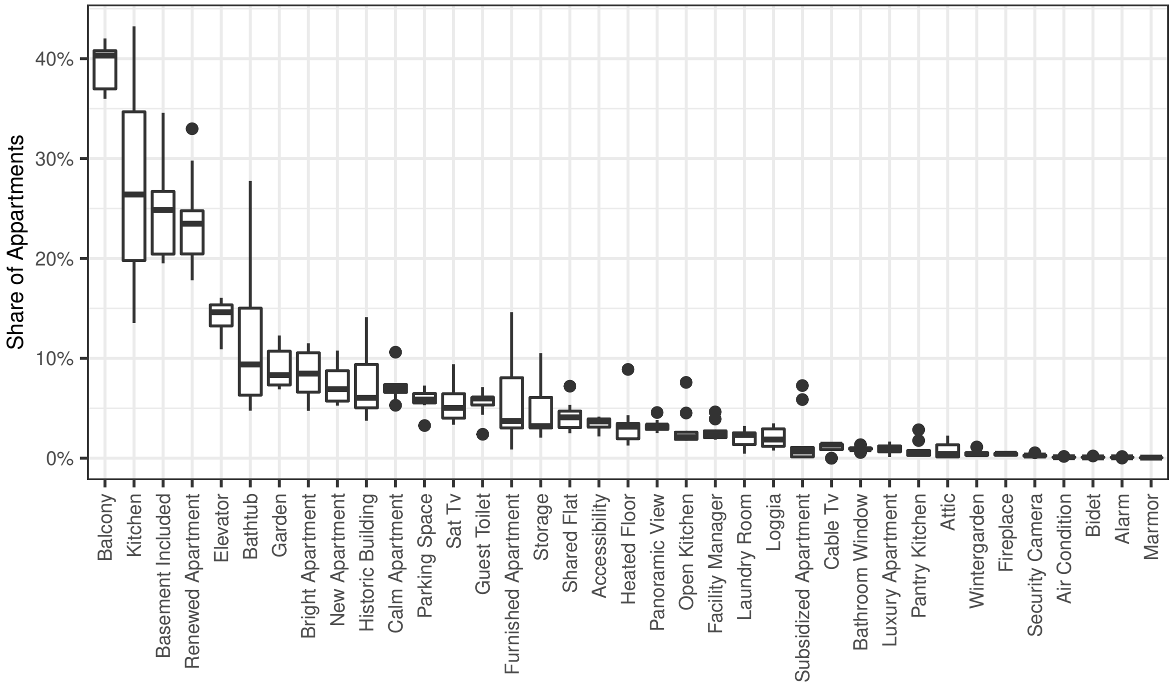

Figure 3.5: *Apartment Characteristics. Own illustration. Data: Own data set*

Munich is significantly higher compared to other cities (see also Figure 3.2). This can also be observed in Figure 3.4 which displays the rent prices per square meter in the different cities. Similar to Figure 3.2 the density distribution of rent prices per square meter is centered around the lowest rent prices per square meter in Dresden and Leipzig. The distribution of rent prices per square meter in Düsseldorf, Cologne, Berlin, Hamburg, and Stuttgart are centered fairly in the middle among the cities in our dataset. Frankfurt am Main and Munich have not only the highest rent prices per square meter but also the highest variation across these prices.

Figure 3.5 gives an overview of the observed apartment characteristics in our data set. This extensive list is gathered from a predefined list of features (e.g., balcony, new) and the description text (e.g. bright, panoramic view) of the advertisements. It can be observed that this encompasses an extensive list of features. However, in most cases a characteristic occurs from the top 10 list (e.g., balcony, basement, kitchen), while other characteristics are only of minor importance. Interestingly, we also observe a notable variation in the occurrence of the top 10 features between different cities. These systematic differences might indicate that the market for rental apartments is also driven by confounders at a local level, such as regulations or path dependencies.

Figure 3.6 gives an overview of how the distance to the next shop (A) or amenity

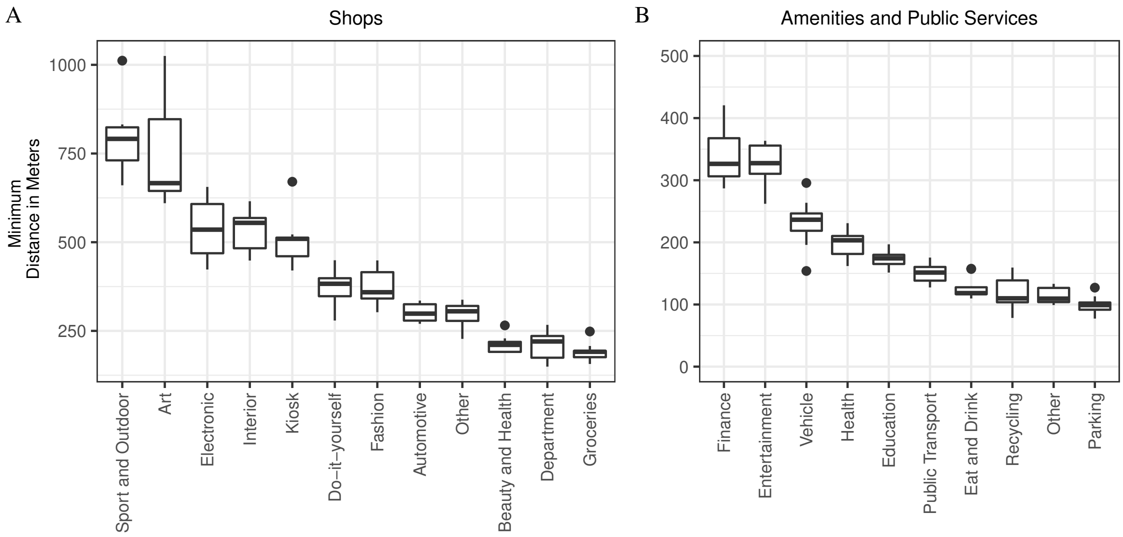

Figure 3.6: *Variation of Minimal Distance from Apartments to Shops as well as Amenities and Public Services between Different Cities. Own illustration. Data: Own data set*

or public services (B) varies for tenants across different cities. It becomes apparent that everyday commodities (e.g., groceries, recycling) can be typically found nearby. In contrast, less frequently visited shops such as electronics or finance are located at further distances. For these types of categories the variation of the average distance is much larger across different cities.

All in all, it can be noticed in the previous figures that a significant heterogeneity is present across cities in our data set. For one, this is important for the identification of the marginal willingness to pay in our econometric model, as this is also identified by the differences between markets. For another, it is important for the external validity of our estimation results, as the marginal willingness to pay is calculated for a varying set of market conditions.

3.4 Econometric Specification and Results

Based on the aforementioned theoretical framework,[10] the first stage of the estimation is specified by the following hedonic price function:

$$\text{price}_{ijt} = \gamma_j \; f\left(\text{traffic}_{ij},\, \lambda\right) + \mathbf{x}'_{ijt}\boldsymbol{\beta}_j + \mathbf{d}'_{ijt}\boldsymbol{\delta}_j + \xi_{ijt} \tag{3.11}$$

where price_{ijt} denotes the deflated price for apartment i in market j at time t, traffic_{ij} denotes our measure for potential traffic on the apartment's road, $\mathbf{x}_{ijt}$

[10]See also Section 2.

includes a set of apartment-specific characteristics and different location- and time-specific fixed effects, $\mathbf{d}_{ijt}$ includes distance measures for various types of shops, amenities, and public services as well as to the city center and the next motorway junction, ξ_{ijt} are other unobserved apartment characteristics, and $f(\cdot,\, \lambda)$ is a non-linear transformation that we explain later.[11] In our baseline specification, $\mathbf{x}_{ijt}$ includes a full set of zipcode-year fixed effects.

In our baseline analysis we treat each city as a separate market. For one, they are geographically separated, given that the minimal distance between two cities is 45 km in our data set. For another, we also observe significant differences in various parameters across cities in the descriptive analysis. In an alternative specification we also test the hypothesis that East Germany (Leipzig, Dresden) and West Germany (Berlin, Hamburg, Munich, Frankfurt am Main, Düsseldorf, Cologne, Stuttgart) still constitute separate markets.

Following Bishop and Timmins (2019) and Ekeland et al. (2004) we model the relationship between our variable of interest and the dependent variable in a non-linear fashion. However, economic theory does not suggest a specific functional form which is best suited to model this non-linear relationship. Thus, hedonic models are frequently estimated with a Box-Cox transformation for the amenity of interest. Next to transforming a variable into a normal distribution, it allows us to test for various functional relationships between a variable of interest and the dependent variable (Cropper et al. 1988). More precisely, we define

$$f\left(\text{traffic}_{ij},\, \lambda\right) = \begin{cases} \frac{\mathsf{traffic}_{ij}^{\lambda}-1}{\lambda} & \text{if} \quad \lambda \neq 0 \\ \log\left(\mathsf{traffic}_{ij}\right) & \text{otherwise} \end{cases} . \tag{3.12}$$

Among others, the considered transformation includes commonly used functional forms such as the square-root-, quadratic-, or logarithmic transformation. We try different values for $\lambda \in \{-3, -2.95, ..., 3\} \setminus 1$ and choose the value that maximizes the value of the profile log-likelihood in the second stage.[12] We achieve the maximum value of the profile log-likelihood function for $\lambda = 1.05$.[13]

[11]For details of the apartment characteristics as well as the calculated distances to shops, amenities and public services see also the data description in Section 3.

[12]The corresponding first- and second order derivatives of the hedonic price function are

$$\hat{p}'\left(\text{traffic}_{ij}\right) = \begin{cases} \hat{\gamma}_j \ \text{traffic}_{ij}^{\lambda-1} & \text{if} \quad \lambda \neq 0 \\ \hat{\gamma}_j \ \text{traffic}_{ij}^{-1} & \text{otherwise} \end{cases},$$

$$\hat{p}''\left(\text{traffic}_{ij}\right) = \begin{cases} \hat{\gamma}_j \ (\lambda-1) \ \text{traffic}_{ij}^{\lambda-2} & \text{if} \quad \lambda \neq 0 \\ -\hat{\gamma}_j \ \text{traffic}_{ij}^{-2} & \text{otherwise} \end{cases}.$$

[13]A plot of the negative profile log-likelihood function for different values of λ can be found in

Given that the value of an apartment in our econometric model is derived from its intrinsic value, information on apartment characteristics is particularly important for the analysis. Consequently, 37 apartment characteristics are considered in the regression.[14] Alongside the apartment characteristics, the rent of an apartment is significantly affected by its location. Other papers in the literature on hedonic models typically employ fixed effects at various levels e.g., city, district or zipcode, to account for location-specific differences in the housing market (See also Baranzini et al. 2008). For example, crime rates, distances to shops, amenities or public services may vary significantly between districts and thus affect rent prices. However, it is not unlikely that the value of a location also differs significantly within districts, particular in larger districts. Thus, it is also a contribution of this paper that we account for this by including apartment-specific distance measures to shops, amenities or public services in the analysis. Further, we control for different sets of location and time fixed effects as the development of rent prices and thus the housing market has been undergoing substantial changes in the past years.

In the second stage we estimate the parameters of the marginal willingness to pay by maximizing (3.9). In principle, the approach of Bishop and Timmins (2019) allows us to control for household-specific characteristics in the estimation of the willingness to pay in the second stage of the regression. For example, for our research question it would be interesting to explore how the estimated marginal willingness to pay is affected by household demographics like age, income, or voting behavior. However, apartment-specific household information is generally not available, for instance, due to data protection reasons.

Table 3.1 displays the regression results for the first stage of the estimation based on 533,402 observations and with heteroskedasticity robust standard errors. Consistent with economic theory the relationship between inner-city traffic and the derivative of rental prices is negative in all cities. Overall, it can be observed that the coefficients are estimated fairly precisely, which is important for the identification of the marginal willingness to pay in the second stage. One slight exception is Stuttgart, where the standard error is relatively larger. Given that the fewest observations (n = 12,676) in our data set are from Stuttgart, this may serve as an explanation.

Table 3.2 shows the regression results for the second stage of our estimation. Given that our results are obtained from a two-step estimation procedure, the

the Appendix.

[14]In detail, this includes the following list of apartment characteristics and features: facility manager, storage, balcony, basement, elevator, open kitchen, pantry kitchen, kitchen, barrier free, bathtub, guest toilet, apartment share, garden, historic, new, renewed, furnished, parking, heated floor, subsidized, level, heating, floor, laundry room, sat, bathroom window, luxury, loggia, attic, camera, alarm, winter garden, fireplace, bidet, air condition, marmor, view, calm and bright.

	Coef.	Std. Error	CI 95%
		γ_j	
Berlin	-0.717	0.080	[-0.873; -0.561]
Dresden	-0.752	0.050	[-0.85; -0.655]
Düsseldorf	-0.809	0.127	[-1.057; -0.561]
Frankfurt Am Main	-2.092	0.244	[-2.571; -1.613]
Hamburg	-0.435	0.083	[-0.597; -0.272]
Cologne	-0.581	0.117	[-0.81; -0.352]
Leipzig	-0.525	0.059	[-0.64; -0.41]
Munich	-0.708	0.237	[-1.173; -0.244]
Stuttgart	-0.804	0.396	[-1.58; -0.027]
Markets:		Cities	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode × Year	
Observations:		533,402	

Note: Standard errors are robust to heteroscedasticity.

Table 3.1: *Estimation Results of the Hedonic Price Function (1st Stage) with the Baseline Setup*

reported standard errors are computed based on a non-parametric bootstrap with 200 replications. All our coefficients are highly significant at the 1% level. We observe a very negative city-specific intercept and a substantially smaller but positive slope. Consequently, reductions of the average street capacity have a positive but a decreasing effect on the marginal willingness to pay of a household. Further, the observed city-specific intercepts have a fairly similar magnitude ranging from -20,619 (Stuttgart) to -24.353 (Hamburg).

A strength of the structural model by Bishop and Timmins (2019) is that it also allows us to compute the willingness to pay for non-marginal policy changes. Given that streets can be described as an interconnected network, the effects of a policy intervention cannot be evaluated in isolation. Thus, limiting traffic on a street or even shutting it down is likely to diverge traffic and increase traffic on other streets nearby. Therefore, we evaluate exemplary traffic reductions of 10%, 20%, and 30% for all streets in the city. However, it is acknowledged that for some very small streets, further gains can hardly be realized with further reductions of traffic. Figure 3.7 presents the willingness to pay various exemplary non-marginal traffic reductions. As the values are calculated based on data from the city-specific road network, the values of the x-axis vary to some extent by city. Nonetheless, it can be

	Coef.	Std. Error	CI 95%
Traffic Capacity	1.584	0.471	[0.662; 2.507]
Sigma	8.768	2.599	[3.673; 13.863]
Berlin	-21.805	6.234	[-34.023; -9.587]
Dresden	-22.350	6.415	[-34.922; -9.777]
Düsseldorf	-22.742	6.513	[-35.508; -9.977]
Frankfurt am Main	-22.513	6.445	[-35.146; -9.88]
Hamburg	-24.353	6.992	[-38.057; -10.649]
Cologne	-23.127	6.630	[-36.122; -10.132]
Leipzig	-22.883	6.568	[-35.755; -10.01]
Munich	-22.506	6.449	[-35.146; -9.866]
Stuttgart	-20.619	6.578	[-33.512; -7.727]
Markets:		Cities	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode × Year	
Observations:		533,402	

Note: Estimation results with city specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 3.2: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with the Baseline Setup*

overall observed that the shape of the functions is fairly similar across cities.

Figure 3.3 displays the expected gains for different exemplary traffic reductions for an average household on a yearly basis. Generally, the magnitude of the expected gains is in a fairly similar range, while being smallest for Stuttgart and highest for Frankfurt am Main. Interestingly, the expected gains are already quite significant for small reductions of traffic.

Additionally, we calculate the total average expected gains for different exemplary traffic reductions by city on a yearly basis (Figure 3.4). For this purpose we first calculate the average expected gain for exemplary traffic reductions for each quarter. Then, we assume that the average number of members in a household is two in our data. Thus, the number of households can be derived from the population in each quarter. Finally, the average expected gain in each city can be gleaned by computing the mean expected gain across all quarters and weighting it with the number of households in each quarter. The expected gains by households differ from the total expected gains by city as these account for the capacity of the street network as well as the number of households in each city. Overall, it can be noted that the total

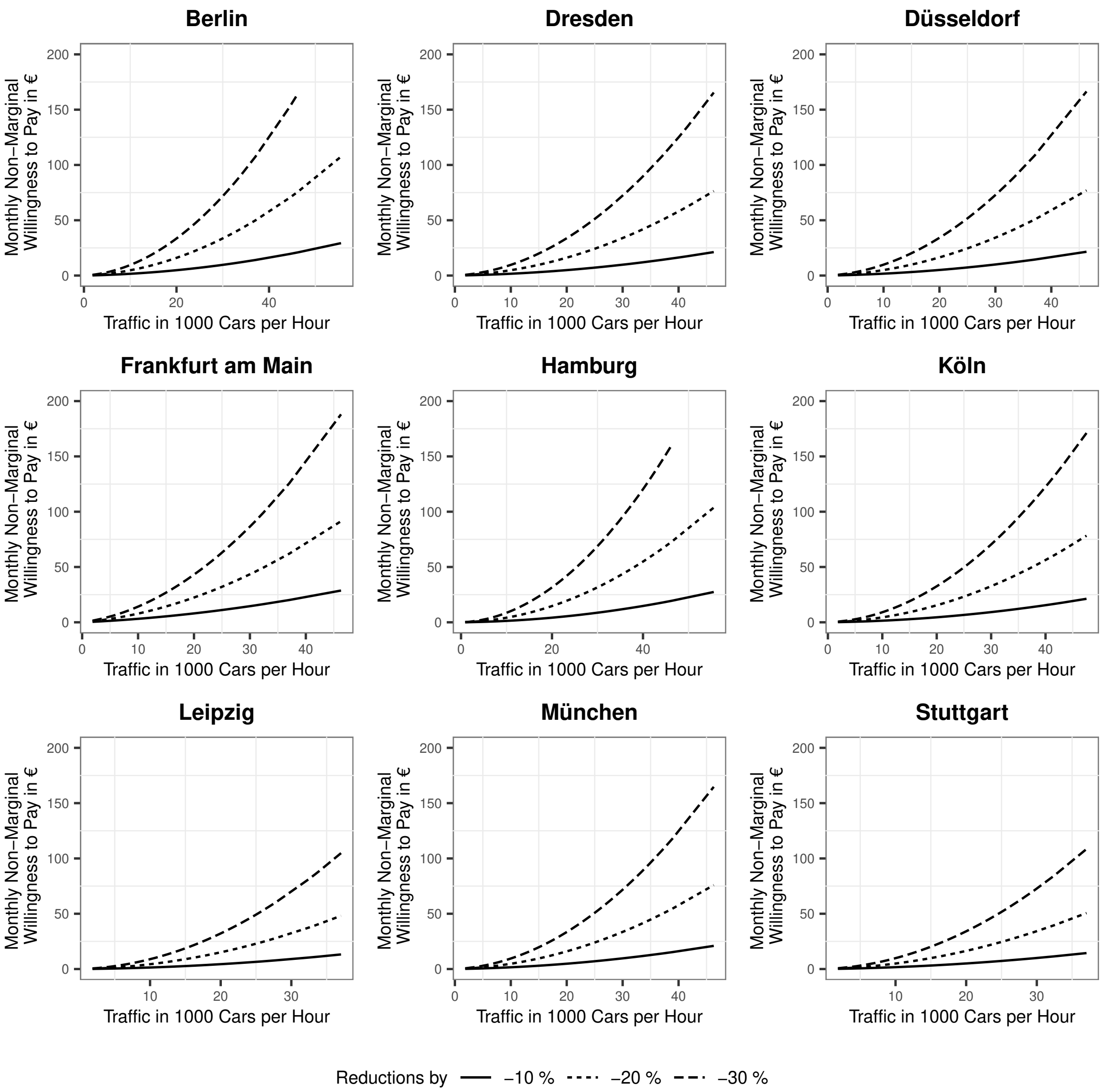

Figure 3.7: *Relationship Between the Monthly Non-Marginal Willingness to Pay per Household and Different Traffic Reductions*

Traffic Reduction	-10 %	-20 %	-30 %
Berlin	32.6	104.4	215.5
Dresden	34.7	110.5	227.6
Düsseldorf	36.6	115.9	237.6
Frankfurt am Main	59.2	158.3	297.4
Hamburg	33.9	118.0	252.0
Köln	33.0	109.6	229.7
Leipzig	30.9	103.5	217.8
München	33.4	107.0	220.8
Stuttgart	30.3	93.8	190.6

Table 3.3: *Non-marginal Willingness to Pay for Different Exemplary Traffic Reductions per Household and Year in Euros.*

Traffic Reduction	-10 %	-20 %	-30 %
Berlin	634 035	2 029 263	4 185 684
Dresden	163 970	524 672	1 082 107
Düsseldorf	229 919	723 694	1 481 325
Frankfurt am Main	459 525	1 223 798	2 292 818
Hamburg	316 951	1 100 094	2 349 430
Köln	209 467	694 436	1 454 908
Leipzig	144 610	484 023	1 018 240
München	1 019 454	3 261 837	6 727 148
Stuttgart	398 046	1 230 718	2 498 014

Table 3.4: *Total Average Expected Yearly Gains in Euros for Different Exemplary Traffic Reductions by City.*

average expected gains by city are more heterogeneous than the average expected gains by household. For example, the expected gains are the highest for Munich, despite being only the 3rd largest city in Germany. Similarly, the expected gains for Stuttgart are fairly large, although the city ranges among the smallest cities in the analysis.

In order to ensure the robustness of the results several checks have been conducted. One important element for the estimation of the willingness to pay is the non-linear relationship between the amenity of interest and the dependent variable. As noted previously, various parameters of λ have been considered in the Box-Cox transformation and thus also different functional forms (see also Figure 3.8 in the Appendix).

Another important element in the estimation of the willingness to pay is the market definition. In the default setup each city is defined as a separate market. Given that all cities vary substantially by size and geographic location it can be argued that this is the most plausible approach. Nonetheless, two alternative market definitions have been considered: In one case each city and year combination is treated as a separate market. It can be observed in Table 3.8 in the Appendix that the magnitude of both the slope and intercept are larger. However, also σ, the variance of the marginal willingness to pay, increases significantly too. This indicates that the marginal willingness to pay is estimated less precisely. Hence, the city-year market definition does not seem to be superior to the default market definition. In another case East and West Germany are defined as separate markets, as 30 years after the German reunification still several differences between the two still persist (BMWi 2019). However, this does not seem to be a useful market definition as the magnitude of the coefficients barely differs between East and West (see Table 3.9

in the Appendix). Consequently, it seems unlikely that this market definition is a better contribution to the model identification than the default market definition.

Further robustness checks include different fixed effects in the hedonic estimation in the first stage of the structural model (tables 3.10 and 3.11). But this changes the results only slightly and in particular raises the standard error of the marginal willingness to pay function. Finally, we consider the mean instead of the minimum as a measure of distances to points of interest. The latter has the advantage because it accounts not only for the distance to the next pub but also from this pub to the pub after that. In that sense this metric can be considered as more precise. Though neither case substantially alters the regression results.

This paper answers an important question, namely what would households pay for a reduction of automobile traffic. Indeed, we also argue that this is the most relevant question for an evaluation of policy measures. What is beyond the scope of this paper is to answer what motivates the individual willingness to pay for a traffic reduction. Are families that are concerned about road safety willing to pay a higher price? Do consumers prefer quiet apartments or cleaner air? What is the role of health concerns related to the externalities of traffic? As the mentioned variables are not modelled explicitly in the estimation it remains unknown what the exact driver for the estimation results is. But answering these questions in a robust empirical framework is far from trivial while the gains for policy-makers may in some cases be limited. For one, prospective tenants typically make their decision based on a bundle of externalities and can hardly distinguish if e.g., more traffic implies more nitrogen dioxide or particulate matter. Second, isolating the causal effect of various externalities which are mutually dependent is empirically challenging. Finally, trying to isolate separate effects of externalities may raise the risk of an omitted variable bias, as all externalities which have an effect on the pricing decision need to be quantified and considered in the analysis.

3.5 Discussion

Our results suggest that households in cities gain from a reduction of automobile traffic. This section discusses possible policy implications and their allocative and distributive effects. Generally, the effects of a policy which aims to reduce traffic are ambilateral.

On the one hand, reducing inner-city traffic raises the utility of residents as it lowers ceteris paribus their exposition to a negative externality. This renders apartments of residents more valuable on the real estate market. For example, families who currently live in the suburb might prefer to live downtown if inner-city automobile traffic is lower. In turn, this utility gain for tenants allows landlords to charge higher rents from their tenants or to sell their property at higher prices on the real estate market. As a consequence, tenants have to pay higher rental prices in exchange for their reduced exposure to automobile traffic and its externalities. Similarly, buyers of property on the real estate market have to pay higher housing prices but gain a more valuable property in exchange. Given that air pollution is particularly an topic in larger cities, where rents have dramatically increased over the past years, this may further ignite housing prices. Further, cities may benefit from higher taxes if the tax yield of property taxes depends on the value of the real estate property (e.g., Germany). If the reduction of automobile traffic raises the utility of tenants, cities may profit from higher rents as this leads to a higher tax income from property taxes.

On the other hand, reducing the street capacity for automobiles also raises ceteris paribus transportation cost for automobiles. This does not only affect the allocation choice of commuters, consumers, and firms. Reducing the street capacity for automobiles renders automobile driving more costly, as it raises ceteris paribus the likelihood of traffic jams. Thus, automobile drivers either have to bear the higher time cost or substitute with another mode of transportation which was previously considered as less attractive relative to automobiles by a rational consumer. In turn, this may also increase the travel costs for other modes of transportation. For one, these costs may be monetary as providers of alternative transportation modes may raise their prices in response to an increasing demand. For another, these costs may also be non-monetary, for example, if traveling on public transport becomes more crowded and thus less comfortable or if increased demand leads to more delays. As a consequence, reducing the street capacity of automobiles may raise inner-city travel costs independent of the mode of transportation.

Commuters would be among the first ones to be affected by higher travel costs. In Germany 68% of the working population commute to their workplace by automobile (Bundesamt für Statistik 2017). In those cities considered for the analysis, on average 46% of a city's working population commutes from the urban hinterland to work. Correspondingly, on average, 27% of the city's working population commute to the urban hinterland.[15] Hence, limiting inner-city mobility affects a significant share of the working population and thus their income opportunities. In addition, it might

[15]In detail, the rounded share of the working population which commutes to and from the city are respectively: Berlin (22%, 14%), Hamburg (36%, 17%), Munich (45%, 28%), Frankfurt am Main (64%, 32%), Cologne (49%, 30%), Düsseldorf (62%, 35%), Stuttgart (60%, 37%), Leipzig (36%, 27%), and Dresden (36%, 25%) Bundesagentur für Arbeit 2019.

also be a locational disadvantage for inner-city firms if their candidates of interest typically commute to their workplace. This is an important issue as, for example, 49% of the medium-sized firms in Germany have stated that they have recruiting problems due to a lack of labor supply (DIHK 2019).

Firms and in particular retail stores may face losses, as these may, depending on the scope of the traffic restrictions, bear higher travel costs for transportation. Indeed, firms may try to pass these higher transportation costs on to consumers if demand for their products is rather inelastic. However, consumers may then prefer to buy their goods for a cheaper price in a local market or the Internet rather than traveling downtown. Thus, besides rendering cities less attractive for commuting workers with lower incomes, raising inner-city travel costs may also render cities less attractive for purchases.

All in all, reducing inner-city traffic from automobiles may involve ceteris paribus noticeable costs and gains. Linking a policy to reduce inner-city traffic from automobiles with other measures to reduce the cost of alternative modes of transportation may help to balance these costs and gains. The results of this paper show that there is a significant and positive willingness to pay for a reduction of traffic. Thus, the externalities from automobile traffic are not only well understood but it is also in the interest of residents. Answering which mode of transportation suits the requirements of a modern city best depends on the individual city-specific context and is beyond the scope of this paper. Finally, cities like Copenhagen or Amsterdam demonstrate how life in cities can be organized with alternative modes of transportation. In both cities more than two thirds of the traffic is conducted with alternative modes of transportation (City of Copenhagen and Administration 2019, van Infrastructuur en Waterstaat 2019).

3.6 Conclusion

In this paper we have estimated the willingness to pay of residents for a reduction of inner-city traffic from automobiles. For this purpose we make use of a novel approach by Bishop and Timmins (2019) which allows us to estimate the willingness to pay without instrumental variables using only moderate econometric assumptions. Our analysis is based on data from nine large cities in Germany between 2016 and 2019 and includes 533,402 detailed observations at the apartment level as well as for various points of interest. Therefore, in the analysis we are able to control for various apartment characteristics and distances measures at a very fine-grained level. To the best of our knowledge this is the first paper which to conduct this analysis for

Germany. We estimate that the non-marginal willingness to pay for a reduction of traffic per household and year ranges by city between €30.3–59.2 for a 10% reduction, €93.8–158.3 for a 20% reduction and €190.6–252 for a 30% reduction. The highest non-marginal willingness to pay for a reduction of traffic is observed in Frankfurt am Main, the lowest in Leipzig. Further, we compute the expected gains for a reduction of traffic at the city level. In addition to the non-marginal willingness to pay for a reduction of traffic, this considers the composition of the road network as well as for the number of households. Accordingly, these expected gains amount between €163,970-1,019,454 for a 10% reduction, €484,023-3,261,837 for a 20% reduction and €1,018,240-6,727,148 for a 30% reduction. The highest expected gains for a reduction of traffic is observed in Munich, the lowest in Leipzig. To ensure the robustness of the results various tests have been conducted. This includes variations of the functional form, the market definition, the control variables, and fixed effects.

Though we observe a significant willingness to pay for a reduction of traffic, the effects of such a policy are ambilateral and its allocative and distributive effects need to be carefully balanced. On the one hand, a reduction of traffic reduces the exposition of apartments to negative externalities and raises the value of these apartments for tenants and owners. But this may also lead to price increases in an already heated housing market. On the other hand, a traffic reduction in cities may ceteris paribus raise the transportation costs of commuters, consumers, and firms. This may render it less attractive to drive to cities for work and purchases and may thus also affect the tax income of cities. Therefore, it might help to link such a policy with other measures which aim to maintain inner-city mobility.

Further research on the willingness to pay for traffic reductions may focus on two topics: To start with, an analysis may complement the results from this study, by broadening the range of different cities in the analysis. This includes nine of the most largest cities in Germany, but currently 57 cities exceed the critical value for air pollution. So the topic of this paper is also an issue that goes beyond the largest cities in Germany. Then, further research may include more detailed information on households, such as demographic information or voting behavior as this may allow us to target policies more precisely to the preferences of consumers and voters.

Bibliography

Baranzini, A., Ramirez, J., Schaerer, C., & Thalmann, P. (2008). *Hedonic Methods in Housing Markets - pricing environmental amenities and segregation*. Springer Science; Business Media.

Bartik, T. J. (1987). The Estimation of Demand Parameters in Hedonic Price Models. *Journal of Political Economy*, *95*(1), 81–88.

Beland, L.-P., & Brent, D. A. (2018). Traffic and crime. *Journal of Public Economics*, *160*, 96–116.

Bishop, K. C., & Timmins, C. (2019). Estimating the marginal willingness to pay function without instrumental variables. *Journal of Urban Economics*, *109*, 66–83.

BMWi. (2019). *Jahresbericht der bundesregierung zum stand der deutschen einheit 2019*. Retrieved June 30, 2020, from https://www.bmwi.de/Redaktion/DE/Publikationen/Neue-Laender/jahresbericht-zum-stand-der-deutschen-einheit-2019.html

Bundesagentur für Arbeit. (2019). Pendleratlas. Retrieved June 30, 2020, from https://statistik.arbeitsagentur.de/DE/Navigation/Statistiken/Interaktive-Angebote/Pendleratlas/Pendleratlas-Nav.html

Bundesamt für Statistik. (2017). Berufspendler. Retrieved June 30, 2020, from https://www.destatis.de/DE/Themen/Arbeit/Arbeitsmarkt/Erwerbstaetigkeit/Tabellen/pendler1.html;jsessionid=ED439C0B4D26A0DF98303DCBD2726BD3.internet712?nn=206552

Bundesbank. (2019). *Monatsbericht februar 2019* (Vol. 71. Jahrgang (2)). Retrieved June 30, 2020, from https://www.bundesbank.de/de/aufgaben/themen/preise-fuer-wohnimmobilien-sind-2018-kraeftig-gestiegen-778630

Carlos, C. M. J., Luc, F., Antonio, S. R., Carlo, L., Miles, P., Frank, R., Francoise, N., Hande, D., Máté, R., Alessandro, D., Marcello, D., & SRI. (2014). *Climate*

Impacts in Europe. The JRC PESETA II Project. Retrieved June 30, 2020, from https://ideas.repec.org/p/ipt/iptwpa/jrc87011.html

City of Copenhagen, T., & Administration, E. (2019). The bicycle account 2018 - copenhagen city of cyclists. Retrieved June 30, 2020, from https://kk.sites.itera.dk/apps/kk_pub2/index.asp?mode=detalje&id=1962

Commission, E. (2018). Eu-kommission verklagt deutschland und fünf weitere mitgliedsstaaten wegen luftverschmutzung. Retrieved June 30, 2020, from https://ec.europa.eu/germany/news/20180517-luftverschmutzung-klage_de

Commission, E. (2019a). Commission takes italy to court over air pollution and failure to properly treat urban waste water. Retrieved June 30, 2020, from https://ec.europa.eu/commission/presscorner/detail/en/IP_19_1475

Commission, E. (2019b). Road transport: Reducing co2 emissions from vehicles. Retrieved June 30, 2020, from https://ec.europa.eu/clima/policies/transport/vehicles_en

Cropper, M. L., Deck, L. B., & McConnell, K. E. (1988). A new approach to consumer theory. *The Review of Economics and Statistics*, *70*(4), 668–675.

Davis, S. C., & Boundy, R. G. (2019). *Transportation energy data book: Edition 37.2*. Retrieved June 30, 2020, from https://tedb.ornl.gov/wp-content/uploads/2019/03/TEDB_37-2.pdf

DIHK. (2019). Arbeitsmarktreport 2019. Retrieved June 30, 2020, from https://www.dihk.de/de/themen-und-positionen/fachkraefte/beschaeftigung/fachkraefteengpaesse-gross-trotz-schwaecherer-konjunktur-5906%22

Economist. (2018). What, and who, are france's "gilets jaunes"? Retrieved June 30, 2020, from https://www.economist.com/the-economist-explains/2018/11/27/what-and-who-are-frances-gilets-jaunes

Economist. (2019). The french president responds to the gilets jaunes. Retrieved June 30, 2020, from https://www.economist.com/europe/2019/04/26/the-french-president-responds-to-the-gilets-jaunes

Ekeland, I., Heckman, J. J., & Nesheim, L. (2004). Identification and estimation of hedonic models. *Journal of political economy*, *112*(S1), S60–S109.

Epple, D. (1987). Hedonic prices and implicit markets: Estimating demand and supply functions for differentiated products. *Journal of Political Economy*, *95*(1), 59–80.

Eurostat. (2019). Passenger cars per 1 000 inhabitants, keyword: Road_eqs_carhab. Retrieved June 30, 2020, from https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=road_eqs_carhab&lang=en

Gartman, D. (2004). Three ages of the automobile: The cultural logics of the car. *Theory, Culture & Society*, *21*(4-5), 169–195.

Gee, G. C., & Takeuchi, D. T. (2004). Traffic stress, vehicular burden and well-being: A multilevel analysis. *Social Science & Medicine*, *59*(2), 405–414.

Glaeser, E. L., & Luttmer, E. F. P. (2003). The misallocation of housing under rent control. *American Economic Review*, *93*(4), 1027–1046.

Greene, W. H. (2012). *Econometric analysis, 7th edition*. Pearson.

Griliches, Z. (1961). Hedonic price indexes for automobiles: An econometric of quality change, 173–196. Retrieved June 30, 2020, from https://www.nber.org/chapters/c6492

Haufe. (2019). Kappungsgrenze für mieterhöhung. Retrieved June 30, 2020, from https://www.haufe.de/immobilien/verwaltung/mietpreisdeckel-regelungen-der-bundeslaender-zur-kappungsgrenze/mietrechtsaenderung-ermoeglicht-laendern-senkung-der-kappungsgrenze_258_275652.html

Houghton, E. (1996). *Climate change 1995: The science of climate change: Contribution of working group i to the second assessment report of the intergovernmental panel on climate change* (Vol. 2). Cambridge University Press.

Kahn, S., & Lang, K. (1988). Efficient estimation of structural hedonic systems. *International Economic Review*, *29*(1), 157–166.

Kholodilin, K. A., Mense, A., & Michelsen, C. (2016). Market Break or Simply Fake? Empirics on the Causal Effects of Rent Controls in Germany. (1584). Retrieved June 30, 2020, from https://ideas.repec.org/p/diw/diwwpp/dp1584.html

Knittel, C. R., Miller, D. L., & Sanders, N. J. (2016). Caution, drivers! Children present: Traffic, pollution, and infant health. *The Review of Economics and Statistics*, *98*(2), 350–366.

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, *74*(2), 132–157.

LBO Baden Württemberg. (2019). Landesbauordnung 6. teil - Einzelne Räume, Wohnungen und besondere Anlagen (§§ 34 - 40).

OECD. (2019). The heavy burden of obesity, 240. Retrieved June 30, 2020, from https://www.oecd-ilibrary.org/content/publication/67450d67-en

Republique Français. (2017). 2018: Tout ce qui va changer. Retrieved June 30, 2020, from https://www.gouvernement.fr/2018-tout-ce-qui-va-changer

Republique Français. (2018). The french president responds to the gilets jaunes. Retrieved June 30, 2020, from https://www.gouvernement.fr/action/plan-climat

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34–55.

Shehab, M., & Pope, F. (2019). Effects of short-term exposure to particulate matter air pollution on cognitive performance. *Scientific reports*, *9*(1), 8237.

Umweltbundesamt. (2019). Liste der städte mit no2-grenzwertüberschreitung. Retrieved June 30, 2020, from https://www.umweltbundesamt.de/dokument/liste-der-staedte-no2-grenzwertueberschreitung

United States Census Bureau. (2017). Sex of workers by means of transportation to work. Retrieved June 30, 2020, from https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=ACS_16_1YR_B08006&prodType=table

Urban Access Regulation. (2019). Urban access regulations in europe. Retrieved June 30, 2020, from https://urbanaccessregulations.eu/

van Infrastructuur en Waterstaat, M. (2019). Mobiliteitsbeeld 2019. Retrieved June 30, 2020, from https://www.kimnet.nl/publicaties/rapporten/2019/11/12/mobiliteitsbeeld-2019-vooral-het-gebruik-van-de-trein-neemt-toe

WHO. (2005). *Health effects of transport-related air pollution*. Retrieved June 30, 2020, from http://www.euro.who.int/en/publications/abstracts/health-effects-of-transport-related-air-pollution

WHO. (2018). *Global status report on road safety 2018*. Retrieved June 30, 2020, from https://www.who.int/violence_injury_prevention/road_safety_status/2018/en/

3.7 Appendix

Statistic	N	Mean	St. Dev.	Min	Max
Art	533,402	1,136.29	1,365.34	0.28	13,574.25
Automotive	533,402	519.37	824.48	0.21	8,836.44
Beauty And Health	533,402	449.43	815.41	0.13	8,001.08
Department	533,402	412.77	768.71	0.09	7,893.65
Do-It-Yourself	533,402	569.94	799.84	0.14	8,453.26
Electronic	533,402	859.67	1,043.52	0.26	12,029.39
Fashion	533,402	655.12	948.96	0.03	11,486.79
Groceries	533,402	408.93	811.55	0.12	8,083.71
Interior	533,402	852.27	1,088.67	0.12	11,282.01
Kiosk	533,402	821.68	1,084.02	0.35	12,145.19
Other	533,402	562.84	893.97	0.04	8,852.33
Sport And Outdoor	533,402	1,105.32	1,101.55	0.67	10,278.46

Table 3.5: *Summary Statistics of Shop Distances*

Statistic	N	Mean	St. Dev.	Min	Max
Townhall	533,402	5,605.75	3,741.04	4.09	19,751.06
Motorway	533,402	3,526.91	2,221.30	1.27	13,856.14
Public Transport	533,402	264.89	540.55	0.21	6,973.58
Eat And Drink	533,402	323.53	749.52	0.08	7,484.79
Education	533,402	357.21	741.61	0.13	7,486.89
Entertainment	533,402	566.29	808.71	0.12	7,610.56
Finance	533,402	574.16	824.10	0.04	7,904.98
Health	533,402	400.15	780.17	0.05	7,817.80
Other	533,402	285.63	721.47	0.05	7,331.73
Parking	533,402	272.89	716.45	0.21	7,319.02
Recycling	533,402	310.36	748.90	0.32	7,564.13
Vehicle	533,402	452.12	765.50	0.93	7,599.45

Table 3.6: *Summary Statistics of Amenity Distances*

Statistic	N	Mean	St. Dev.	Min	Max
Price	533,402	725.53	423.22	150	3,857
Size	533,402	68.42	27.01	17	214
Number of Rooms	533,402	2.37	0.92	1	8
Number of Lanes	533,402	1.93	0.45	1	6
Maxspeed in Street	533,402	37.77	9.91	5	100
Facility Manager	533,402	0.03	0.17	0	1
Storage	533,402	0.05	0.22	0	1
Balcony	533,402	0.39	0.49	0	1
Basement included	533,402	0.25	0.43	0	1
Elevator	533,402	0.15	0.36	0	1
Open Kitchen	533,402	0.03	0.18	0	1
Pantry Kitchen	533,402	0.01	0.10	0	1
Kitchen	533,402	0.25	0.44	0	1
Accessibility	533,402	0.03	0.18	0	1
Bathtub	533,402	0.15	0.36	0	1
Guest Toilet	533,402	0.05	0.22	0	1
Shared Flat	533,402	0.05	0.21	0	1
Garden	533,402	0.09	0.29	0	1
Historic Building	533,402	0.09	0.29	0	1
New Apartment	533,402	0.07	0.26	0	1
Renewed Apartment	533,402	0.27	0.44	0	1
Furnished Apartment	533,402	0.04	0.20	0	1
Parking Space	533,402	0.05	0.23	0	1
Heated Floor	533,402	0.04	0.19	0	1
Subsidized Apartment	533,402	0.03	0.17	0	1
Laundry Room	533,402	0.02	0.13	0	1
Sat TV	533,402	0.06	0.24	0	1
Cable TV	533,402	0.01	0.09	0	1
Bathroom Window	533,402	0.01	0.10	0	1
Luxury Apartment	533,402	0.01	0.09	0	1
Loggia	533,402	0.02	0.14	0	1
Attic	533,402	0.01	0.08	0	1
Security Camera	533,402	0.003	0.05	0	1
Alarm	533,402	0.001	0.03	0	1
Wintergarden	533,402	0.01	0.08	0	1
Fireplace	533,402	0.004	0.06	0	1
Bidet	533,402	0.001	0.03	0	1
Air condition	533,402	0.001	0.03	0	1
Marmor	533,402	0.0005	0.02	0	1
Panoramic View	533,402	0.03	0.18	0	1
Calm Apartment	533,402	0.07	0.25	0	1
Bright Apartment	533,402	0.07	0.26	0	1

Table 3.7: *Summary Statistics of Appartment Characteristics (See also Section 3 for their origin)*

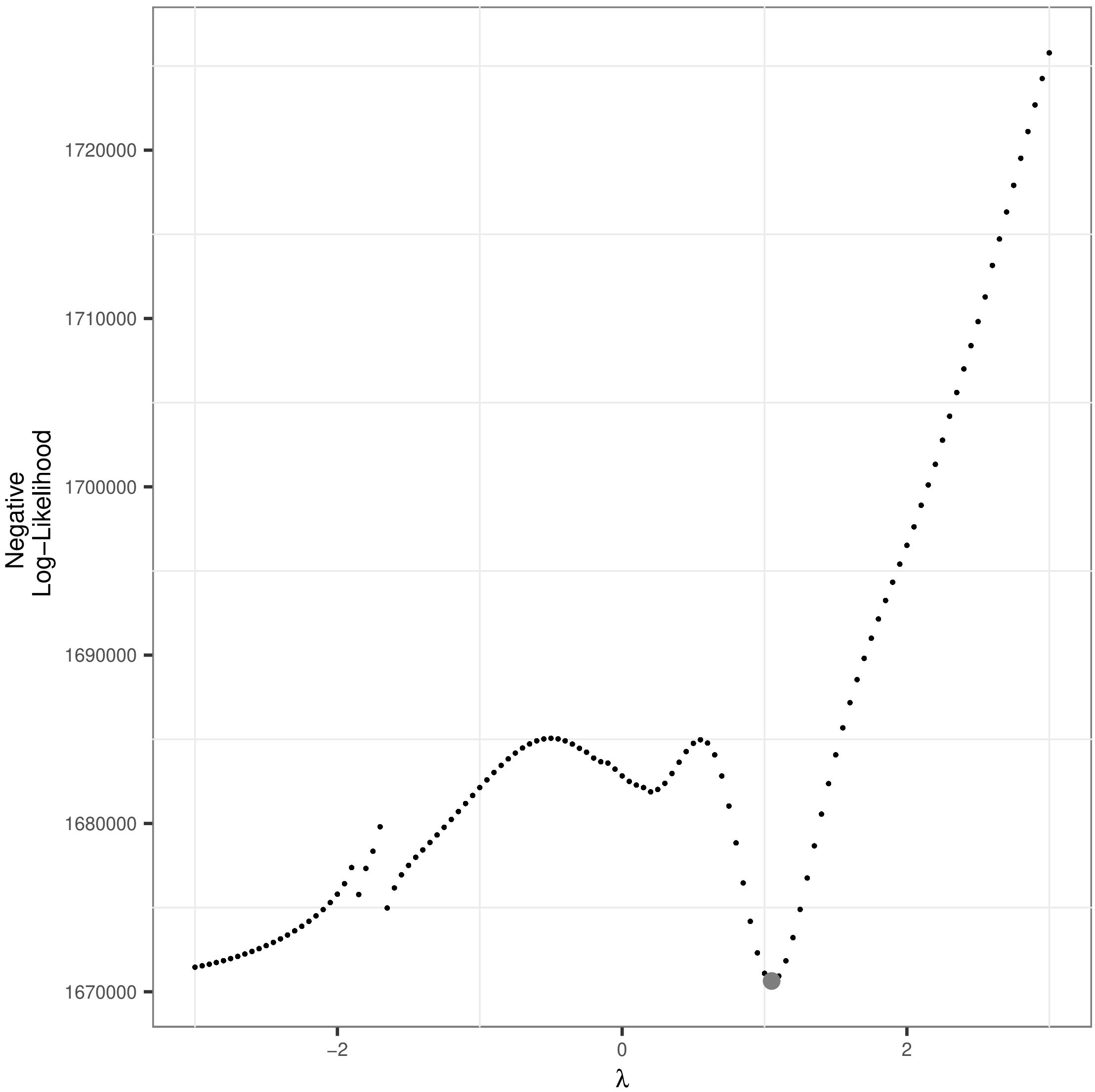

Figure 3.8: *Relationship between the λ-Value in the Box-Cox Transformation and the Negative Log-Likelihood in the Maximum-Likelihood Estimation in the Second Stage of the Estimation with the Baseline Setup as reported in Tables 3.1 and 3.2.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	2.224	0.082	[2.064; 2.384]
Sigma	12.300	0.437	[11.442; 13.157]
Berlin2016	-30.462	1.412	[-33.229; -27.695]
Berlin2017	-30.113	1.698	[-33.441; -26.786]
Berlin2018	-30.696	1.617	[-33.865; -27.527]
Berlin2019	-29.955	1.587	[-33.065; -26.844]
Dresden2017	-31.320	1.660	[-34.573; -28.066]
Dresden2018	-31.369	1.485	[-34.28; -28.459]
Dresden2019	-30.828	1.631	[-34.024; -27.631]
Düsseldorf2016	-33.429	2.385	[-38.104; -28.754]
Düsseldorf2017	-31.307	1.554	[-34.352; -28.261]
Düsseldorf2018	-31.690	1.615	[-34.856; -28.524]
Düsseldorf2019	-31.481	1.481	[-34.383; -28.578]
Frankfurt Am Main2016	-31.290	1.674	[-34.571; -28.009]
Frankfurt Am Main2017	-31.255	1.958	[-35.093; -27.417]
Frankfurt Am Main2018	-31.601	1.423	[-34.389; -28.812]
Frankfurt Am Main2019	-31.093	1.738	[-34.5; -27.686]
Hamburg2016	-34.017	2.206	[-38.341; -29.693]
Hamburg2017	-33.889	1.937	[-37.685; -30.094]
Hamburg2018	-34.228	1.575	[-37.315; -31.141]
Hamburg2019	-33.568	1.621	[-36.746; -30.391]
Cologne2016	-32.511	2.019	[-36.468; -28.553]
Cologne2017	-32.106	1.563	[-35.169; -29.043]
Cologne2018	-32.292	1.821	[-35.86; -28.723]
Cologne2019	-32.085	1.460	[-34.945; -29.224]
Leipzig2017	-31.769	1.675	[-35.052; -28.487]
Leipzig2018	-32.191	1.735	[-35.592; -28.791]
Leipzig2019	-31.418	1.640	[-34.632; -28.204]
Munich2016	-31.244	1.903	[-34.973; -27.514]
Munich2017	-30.964	1.485	[-33.874; -28.054]
Munich2018	-31.673	1.531	[-34.673; -28.673]
Munich2019	-31.198	1.562	[-34.259; -28.137]
Stuttgart2016	-29.699	1.718	[-33.067; -26.332]
Stuttgart2017	-28.821	1.973	[-32.689; -24.953]
Stuttgart2018	-28.583	1.715	[-31.945; -25.221]
Stuttgart2019	-28.301	1.756	[-31.742; -24.859]
Markets:		City × Year	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode × Year	
Observations:		533,402	

Note: Estimation results with city-year specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 3.8: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with City and Year as Markets.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	0.065	0.044	[-0.022; 0.152]
Sigma	0.372	0.247	[-0.112; 0.857]
West	-1.745	0.632	[-2.985; -0.506]
East	-1.736	0.637	[-2.983; -0.488]
Markets:		East and West Germany	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode $\times$ Year	
Observations:		533,402	

Note: Estimation results with region specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 3.9: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with East and West Germany as Markets.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	1.955	0.570	[0.838; 3.073]
Sigma	10.817	3.151	[4.64; 16.993]
Berlin	-26.647	7.538	[-41.421; -11.872]
Dresden	-27.347	7.756	[-42.549; -12.145]
Düsseldorf	-27.806	7.878	[-43.246; -12.365]
Frankfurt am Main	-27.520	7.799	[-42.806; -12.235]
Hamburg	-29.782	8.457	[-46.357; -13.207]
Cologne	-28.273	8.002	[-43.957; -12.589]
Leipzig	-27.992	7.940	[-43.555; -12.429]
Munich	-27.505	7.805	[-42.802; -12.209]
Stuttgart	-25.170	7.953	[-40.758; -9.582]
Markets:		City	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode + Year	
Observations:		533,402	

Note: Estimation results with city specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 3.10: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with Zipcode and Year Fixed Effects.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	1.951	0.581	[0.811; 3.09]
Sigma	10.791	3.215	[4.491; 17.092]
Berlin	-26.570	7.690	[-41.641; -11.498]
Dresden	-27.280	7.910	[-42.784; -11.777]
Düsseldorf	-27.728	8.034	[-43.476; -11.981]
Frankfurt am Main	-27.443	7.955	[-43.034; -11.852]
Hamburg	-29.695	8.624	[-46.598; -12.791]
Cologne	-28.192	8.159	[-44.183; -12.2]
Leipzig	-27.918	8.097	[-43.789; -12.048]
Munich	-27.421	7.959	[-43.02; -11.822]
Stuttgart	-25.089	8.114	[-40.991; -9.186]
Markets:		City	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Minimal Distance	
Fixed Effects:		Zipcode	
Observations:		533,402	

Note: Estimation results with city specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 3.11: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) with Zipcode Fixed Effects.*

	Coef.	Std. Error	CI 95%
Traffic Capacity	1.545	0.426	[0.711; 2.38]
Sigma	8.552	2.354	[3.938; 13.165]
Berlin	-21.250	5.647	[-32.317; -10.182]
Dresden	-21.802	5.814	[-33.196; -10.407]
Düsseldorf	-22.182	5.903	[-33.752; -10.612]
Frankfurt am Main	-21.964	5.842	[-33.413; -10.515]
Hamburg	-23.767	6.334	[-36.181; -11.352]
Cologne	-22.554	6.006	[-34.327; -10.782]
Leipzig	-22.333	5.951	[-33.998; -10.669]
Munich	-21.945	5.843	[-33.396; -10.493]
Stuttgart	-20.121	5.954	[-31.79; -8.452]
Markets:		City	
Apartment Characteristics:		All	
Shops, Amenities & Public Services:		Mean Distance	
Fixed Effects:		Zipcode × Year	
Observations:		533,402	

Note: Estimation results with city specific intercept. Standard errors are obtained by a non-parametric bootstrap with 200 replications.

Table 3.12: *Estimation Results of the Marginal Willingness to Pay Function (2nd Stage) and Mean Distances to Shops, Amenities and Public Services.*

Contributions of Nicolas Wellmann to the paper 'What Would Households Pay for a Reduction of Automobile Traffic? Evidence From Nine German Cities':

- Jointly developed the idea for the paper and the gathering of the real estate data
- Organized, monitored and maintained the ongoing collection and archival of the real estate data
- Gathered and matched the *Openstreetmap* data
- Jointly cleaned the full dataset and developed the empirical estimation strategy
- Conducted the estimations with various robustness checks
- Researched the literature
- Created the descriptive statistics and plots for the paper
- Wrote the paper (Introduction, Econometric Model, Data, Econometric Specification, Discussion, Conclusion, Appendix)
- Jointly proofread the paper

Düsseldorf, 1. September 2020 ____________________________
Daniel Czarnowske (Co-Author)

Chapter 4

Market Structure and Mobile Network Quality - An Empirical Analysis

4.1 Introduction

A popular claim in mobile merger cases is that consolidation raises investments into mobile networks: For example, T-Mobile US/Sprint (2018) and Telefónica Germany/E-Plus (2014) argued in the investigation of their merger that it will lead to a faster roll-out of their mobile networks (European Commission 2014, T-Mobile US 2018). Indeed, Hutchison 3G Italy/Wind (2016) stated in their merger that neither firm has sufficient resources to compete with the mobile networks of the other two market players (European Commission 2016a). Interestingly, this issue has also gained relevance in merger investigations by the European Commission. While previous investigations[1] were focused on prices, more emphasis has been put on quality of mobile networks since the Hutchison 3G Italy/Wind (2016) merger: "Today's decision ensures [...] that consumers can continue to enjoy innovative mobile services at fair prices and on high quality networks." More generally, this topic has attracted not only the interest of business and policymakers[2] it also relates to a wider discussion in competition policy: Does a lower market concentration lower price levels but at the cost of a lower mobile network quality?

Answering this question is relevant for various M&A which have been observed in the past years which coincide with economic and political changes.[3] Economically, the maturing demand for mobile telecommunication services is challenging the industry as it limits the opportunities for additional growth and revenues. Additionally, mobile users have shifted to over-the-top services like Facebook or WhatsApp and have raised demands for mobile data services quantitatively and qualitatively (see also Peitz and Valletti 2015). Politically, the European Union is aiming for a harmonization of mobile markets as part of its agenda for a joint digital market in the EU (European Commission 2019). This includes, for example the regulation of roaming fees, which steadily decreased in the past, and the convergence of data protection laws into the General Data Protection Regulation (European Union 2016a, European Union 2016b). In European and US mobile markets competition mostly takes place between three or four mobile network operators (MNO). Thus, among decision-makers the question in the room is: Is the optimal number of MNOs in the mobile market three or four? Past merger decisions in the EU suggest that competition policy is

[1]See, for example, the press statements of the EU commissioner for competition in previous merger decisions: TeliaSonera/Telenor 2015, H3G United Kingdom/Telefónica UK 2015 or H3G Austria/Orange AT 2012.

[2]For example, OECD 2014, HSBC 2015, GSMA 2017, Frontier Economics 2015.

[3]For example, T-Mobile US/Sprint 2020, T-Mobile NL and Tele2 NL 2018, H3G Italy/Vimpelcom 2016, H3G Ireland/Telefónica IE 2014, Telefónica Germany/E-Plus 2014, H3G Austria/Orange AT 2012.

somewhat indecisive regarding the answer: While some four to three mergers have been blocked, others have been allowed, but often with remedies which enable the direct entry of a new market player.[4]

Answering this question is also relevant for various 5G auctions which are ongoing or upcoming in different countries. First of all, the outcome of spectrum auctions may significantly alter the spectrum endowment of market players and thus affect their future development. For example, Telefónica Germany/E-Plus (2014) motivated their merger with the competitive disadvantage that E-plus failed to acquire a 4G license in the 800 MHz band (European Commission 2014). Second, regulators can set several rules regarding the deployment and upgrade of mobile networks. These may include rules on the deployment of base stations or coverage of areas with certain speeds. Depending on the nature of the regulation these may also lower or raise the incentives for market entry. For instance, the German 5G spectrum auction included relaxed rules for new market entrants (Bundesnetzagentur 2018). Subsequently, a new market entrant has acquired 5G spectrum.

According to a report by the European Commission (2018), 97.9% of EU-households were covered by 4G networks in 2017. But nonetheless various areas exist where connectivity is slower or not available at all. For one, the demand for mobile services is not only restricted to households and it also includes traffic routes or commercial areas. For another, this includes rural areas where 4G coverage reaches only 89.9% of EU households. Certainly, investments in mobile networks are costly and thus subject to a critical cost-benefit analysis by MNOs. But these discrepancies in costs cannot explain why significant differences in connectivity persist between different countries. It seems surprising that LTE coverage in economies like Germany, France or the UK is lagging behind countries where geography makes running a mobile network costly (e.g., low population density in Scandinavian countries or topography in Switzerland) or with fewer financial resources (e.g., Eastern European countries).[5]

Access to mobile services is highly relevant for both consumers and businesses. For example, the European Competition Commission stressed in the merger of Hutchison 3G Italy/Wind (2016): "Mobile telecom services are increasingly important in our daily lives. We use our mobile phones not only to get in touch with our family and friends but also to read the news, shop online or check the train schedule.

[4]For example the merger between H3G United Kingdom/Telefónica (UK 2015) as well as TeliaSonera/Telenor (2015) were blocked while the H3G Italy/Vimpelcom (2016) merger has been approved subject to remedies which enabled the market entry of the MNO Iliad.

[5]Actually the state of mobile coverage in Germany led the German Minister of Economic Affairs to admit that he avoids mobile calls from foreign politicians as he is too embarrassed about the poor mobile network infrastructure in his country (Der Spiegel 2018).

[...]" (European Commission 2016b). Moreover, 96% of large enterprises in the EU provide employees with mobile devices and 44% of these are for dedicated business applications (Eurostat 2017). All these examples rely on fast, reliable, and affordable access to mobile networks. This is likely to gain further importance with upcoming 5G applications such as telehealth, self-driving cars or the Internet of things.

Recent papers in the literature have found that a higher market concentration may actually raise investments in mobile networks (Jeanjean and Houngbonon 2017, Houngbonon and Jeanjean 2016, Genakos, Valletti, and Verboven 2018). To the best of our knowledge this paper is among the first to analyze how market structure affects mobile network quality. The analysis is based on quarterly data from 49 MNOs from 14 European countries between 2011 and 2016. It makes use of different quality measures which are calculated based on 500 million measurements of mobile network quality. First, one main result of this paper suggests that a higher market concentration seems to improve different measures for mobile network quality. Interestingly, this effect is observed at both the firm and also on the market level. Second, the other main result is that late entrants seem to provide a higher share of 3G and 4G connections and connections with different minimum speeds than market incumbents. Market incumbents seem to provide higher maximum speeds instead. Generally, the findings of this paper add to the recent literature which observes a negative relationship between market concentration and investments and confirms this also with respect to mobile network quality. Given that there is considerable evidence in the price-concentration literature[6] that a higher market concentration may raise prices, the results of this paper may imply that regulators face a potential trade-off: Either they aim for lower prices or for a higher mobile network quality.

The remainder of the paper is as follows: Section 2 gives an overview of related literature on the mobile telecommunication market. Section 3 describes the data used in the analysis. Section 4 outlines the econometric setup. Section 5 presents and discusses the estimation results. Section 6 concludes.

4.2 Related Literature

According to Aghion and Tirole (1994) the two most relevant research questions in industrial organization are: How does competition affect prices and how does competition affect investments? This paper relates to both topics. This section will start with selected theoretical insights which cover both topics jointly. Then we subsequently focus on selected empirical papers in each of these literature streams.

[6]See also the related literature in Section 4.2.

Finally, this section covers the limited literature on the relationship between market structure and quality of services.

Some findings in the theoretical literature note that a lower market concentration lowers prices and raises investments in the industry. For example, Motta and Tarantino (2017) study horizontal mergers in a game theoretic approach. In their model firms simultaneously choose prices and cost-reducing investments. They find that merging parties reduce investments and raise prices. At the same time outsiders of the mergers raise investments and either increase or decrease their prices. However, at the aggregate market level the authors observe that mergers harm consumers due to higher prices and lower industry investments, absent significant efficiency gains. Their results remain robust if they consider quality-enhancing investments instead and for different types of demand functions. Federico et al. (2018) obtain similar findings, but with a different approach. They employ an oligopoly model where innovation is stochastic and raises the quality of products. This allows to study the interaction between price coordination and investment externalities and their effects on investments. They find that a merger raises prices and lowers overall innovation.

Other theoretical papers suggest that the relationship between market structure and investments is indeed more ambiguous. Vives (2008) studies the relationship between different measures of market structure and innovation in Bertrand and Cournot models. He finds that raising the number of firms in a market tends to lower the money spend on cost reductions or quality improvements. Furthermore, he observes that investments per firm are higher in larger markets. Schmutzler (2013) considers various oligopoly models in a two-staged framework to determine how competition affects cost-reducing investments in different scenarios. Accordingly, the relative efficiency of a firm raises the probability that competition will have a positive effect on investments. Contrary rising spillover effects make a negative effect of competition on investments more likely. The level of competition in a market has an ambiguous effect on investments. Bourreau and Jullien (2018) use a model similar as Motta and Tarantino (2017) but delineate a specific case where a merger actually has a positive effect on investments, total coverage, and consumer surplus. Marshall and Parra (2019) describe specific circumstances in which a reduction of competition raises innovation in the industry and welfare in the long run.

Empirical papers on the relationship between market structure and prices originally evolved from to the conduct-structure-performance literature (e.g., Chamberlin 1933, Mason 1939, Bain 1951). The latter approach is subject to various criticism, for example by Schmalensee (1989): First, the reliance on profit measures from accounting data is problematic as it might be subject to tax-strategic considerations.

Second, the analysis of profits and market structure is subject to an endogeneity problem: A lower market concentration may raise profits, but this may also backfire on the market structure by raising incentives for market entry. Third, the analysis of a broad set of industries renders the interpretation of the results problematic. Consequently, the analysis has shifted from the conduct-structure performance approach to market-specific price-concentration studies. These studies have been applied to a wide range of markets: e.g., gasoline (Oladunjoye 2008), airlines (Giaume and Guillou 2004), banking (Focarelli and Panetta 2003), electricity (Chang and Park 2007), beer (Ashenfelter et al. 2015), groceries (Asplund and Friberg 2002) and telecommunication markets (Sung 2014). Furthermore, the popularity of price-concentration studies is also reflected in investigations of competition authorities.[7] A common finding of these studies is that a higher market concentration raises the price level of a market. However, Bresnahan (1989) and Schmalensee (1989) point out that price-concentration studies are bound to similar endogeneity problems as the conduct-structure-performance literature. Naturally, as profits are a function of prices, these are also subject to feedback effects from changes in the market structure. To address this endogeneity problem Evans et al. (1993) suggest conducting a fixed effects estimation with instrumental variables. Furthermore, reduced form models have become the workhorse in price concentration studies due to their applicability to a wide range of analysis (Baker and Rubinfeld 1999).

Empirical papers on the relationship between market structure and investment in innovations date back to a long discussion in the economic literature: Schumpeter (1942) hypothesizes that monopolies have better resources and higher incentives to innovate as this allows them to gain monopoly profits. Instead Arrow (1962) argues based on a formal analysis that competition provides higher incentives to innovate. Cohen and Levin (1989) and later Gilbert (2006) review the extensive literature in this debate (e.g., Aghion, Bloom, et al. 2005, Blundell et al. 1999, Nickell 1996) and conclude that the literature is far from developing a general theory on how competition affects innovation. Though Gilbert (2006) finds that R&D investments increase with the firm size up to some boundary, there is neither substantial evidence that this also applies to process innovations nor that competition augments product innovation. At least Sutton (1996) notes there is a widespread consensus in the literature that both variables are determined endogenously.

With the large merger wave in the mobile industry, the relationship between market structure and investments has also attracted interest in the recent mobile

[7] See, for example, the European Union (2012), European Union (2013b), European Union (2013a).

telecommunication literature. For example, Genakos, Valletti, and Verboven (2018) conduct a study based on 33 OECD countries between 2002 and 2014. Interestingly, they investigate how both prices and investments are affected by variations in the market structure. Their findings suggest that competition authorities face a potential trade-off when deciding in mergers. Accordingly, a hypothetical merger from four to three MNOs, increases prices for consumers by 16.3% but raises capital expenditures per operator by 19.3%. However, they do not observe these results at the market level. Houngbonon and Jeanjean (2016) find that competition has a maximum effect on investments if the operator's gross profit accounts for 37% or 40% of their revenues.[8] Below this threshold there is a trade-off between competition and investments. A similar analysis is conducted by Jeanjean and Houngbonon (2017) which is based on both theoretical and empirical elements. They observe a positive effect of competition on investments only in the short run. In the long run this effect turns negative with a magnitude which is three to four times larger than the short-run effect. Additionally, they observe a negative effect on investments in symmetric markets.

Generally, the aforementioned papers provide important insights on how variations in market structure affect investments in the mobile market. But it remains unknown how these variations in market structure finally transmit into a better mobile network quality and thus benefit consumers: First, these studies use capital expenditures as a measure, but this might be biased. Given that this variable is gathered from accounting data it is subject to tax strategic considerations, which is also a criticism of the structure-conduct-performance literature. Second, as noted in Genakos, Valletti, and Verboven (2018), capital expenditures only include investments made in all types of physical assets. While this is certainly an important driver for network quality, there are also other important explanatory variables. For example, maintenance efforts may also improve network quality, but these are not considered in the analysis as they account to personnel expenditures. Third, the influence of investments depends not only on the magnitude, but also on the efficiency of investments. Stoughton et al. (2017) suggest that the efficiency of investments depends on the market structure and that efficiency is actually lower in competitive markets. If this applies to the mobile market, mobile network quality depends not only on the magnitude of investments but also on their efficiency. Finally, it remains unknown what the underlying functional relationship between investments and mobile network quality is.

To the best of our knowledge, only few studies focus on the direct relationship between market structure and quality of service in the mobile telecommunication

[8] This depends on the normalization of capital expenditures.

market. For example Yun et al. (2018) studies only the latter to estimate a hedonic price index for 12 selected metropolis in 10 different countries. They observe significant differences in the magnitude of their price index if they also account for quality measures such as tariff characteristics or connectivity speeds. This underlines that mobile network quality can significantly vary between different countries. Faccio and Zingales (2019) study the political determinants of competition in the mobile industry. For this they make use of a cross-sectional dataset with up to 145 countries. Among others, they regress a regulatory score against different quality measures, such as the share of 3G and 4G connections. They observe a positive effect of the regulatory score and conclude that more competition does not decrease coverage or quality in general. However, as the regulatory score is rather generic, it remains unknown what parameters of market structure influence mobile network quality.[9] Furthermore, their cross-sectional data set rules out panel methods which may account for important differences in unobserved heterogeneity across countries.

4.3 Data Description

For the analysis we focus on European countries, as these are bound to a similar economical, regulatory, geographical, and technical background. In total we use 500 million measurements on network connectivity to compute different measures for mobile network quality on a quarterly basis.[10] For the investigation these are matched with various economic and regulatory indicators from 49 MNOs from 14 European countries.

Assessing the quality of mobile networks is a challenging task, as the observed connectivity is subject to various confounding influences. For example, if a call is initiated from a mobile phone it needs to be sent to the base station of the cellular network before being transported via the backbone of the MNO, where it is then routed via the telephony network and finally transmitted to the recipient. Here the connectivity does not only depend on conditions which affect the transmission of the wireless signals, like weather, terrain or speed of movement. The connectivity may also be affected by congestions in the mobile cell, in the backbone of the MNO, as well as the connection to and the connectivity within the foreign telephony network itself.[11] Though these variables may significantly affect connectivity, these are only

[9] The score measures, for example, the degree of competition (monopoly, partial competition, ...) and if the regulator is independent.

[10] Namely these countries are Austria, Croatia, Czech Republic, Germany, Hungary, Italy, Ireland, France, Netherlands, Romania, Slovakia, Spain, the United Kingdom, and Norway. Number of measurements rounded.

[11] For details, on the functionality of mobile telecommunication networks see, for example, Gruber

partially under the control of the MNO or related to competition in the market.

To address the aforementioned difficulties, our analysis is based on a large-scale dataset which is collected during real-world mobile phone usage. The data is collected from the crowdsourcing app *Device Analyzer* which is available for free in the Google Playstore. It continuously logs all kinds of smartphone activities in the background and provides users in turn with statistics on their usage (Wagner et al. (2013), Wagner et al. 2014). Given that the data is collected from real-world phone usage, it includes all types of situations which typically affects the connectivity of mobile phone users: e.g., urban and rural areas, different weather conditions or different driving speeds. Moreover, due to the large scale of the dataset a significant number of measurements for various MNOs during a longer time period is ensured.

Compared to dedicated speed test apps or websites, our dataset provides a further advantage for the analysis. Typically, apps on smartphones are installed on a voluntarily basis. Consequently, app usage is subject to some selection mechanism. If this selection is based on network connectivity, then the data is subject to a sample selection bias. This is likely the case for data from dedicated speed test apps or websites. Users which face a repeatedly low connectivity might be more inclined to use a speed test app to investigate this issue in detail. Consequently, network connectivity based on this sample, may be lower than it actually is. A similar case is likely for users with a particular high connectivity, which may then lead to an upward bias of network connectivity. In contrast, our data is collected by a general purpose app which provides all kinds of statistics to users. This renders it unlikely that the data is subject to a sample selection bias.

In the analysis we focus on wireless coverage, i.e., the standard of mobile broadband connection and signal strength. Firstly, wireless coverage is a major determinant in mobile connectivity. Secondly, as it is displayed in real time to smartphones users, it is likely to be a major element for how network quality is perceived by consumers and thus influences competition between MNOs. Furthermore, we focus only on mobile connections based on the GSM standard, since this is the dominating standard in Europe. In order to fully exploit the geographical coverage of our measurements, we use a two-step aggregation procedure. Initially we use the collected information on wireless coverage to calculate for each operator average access speeds by mobile cell and quarter. Then, different measures for mobile network quality are calculated by operator and quarter as a centered rolling average. These are namely the share of mobile network connections with 3G and 4G, the share of connections which exceed 1Mbps, 2Mps, 3Mbps as well as the maximum speed. Compared to a direct

(2005) chapter 2.2.

calculation of these measures across all observations, the two-step procedure has the advantage of ruling out that our measurements are driven by few but popular locations. Failing to account for this may significantly distort the aggregation if measurements in these popular locations deviate significantly from other observations. Furthermore, 1% of the observations with the bottom and top speeds are dropped to rule out the influence of extreme outliers. As part of the aforementioned procedure we also compute the mean of the number of wireless access points for each mobile cell and quarter. We use this information as a proxy to control for the degree of urban density in the estimation.

Market data such as the number of competitors in each country, subscriber numbers, the market entry position as well as subsidiaries in the European market are gathered from financial statements of MNOs, market reports of regulatory authorities, and also Gruber (2005). Information on the GDP per capita and population size, which is used as a proxy variable for market size in the regression, is collected from Eurostat. Mobile termination rates are obtained from BEREC.[12] Based on the total number of post-paid and prepaid subscribers we calculate the Herfindahl-Hirschman-Index (HHI) for each country and quarter.[13] Moreover, we calculate for each country the mean number of multimarket contacts of the operating MNOs via subsidiaries in other European countries: First, the number of multimarket contacts is calculated per MNO and time period, then the average of this result for each mobile market and time period. For the analysis we focus on those countries where most of the signal measurements were taken and matched this with the market data. Unfortunately, this data is not consistently available over time, particularly for smaller MNOs and countries.

A notable difference between the network connectivity data and market data is the aggregation level. While the former is available by date, time and mobile cell, the latter is typically aggregated on a quarterly basis at the national level. Given that both competition between MNOs and the regulation of MNOs, takes place at a national level this is not a shortcoming for the investigation. But, the nature of how this data is generated rules out an analysis of these variables at a more disaggregate level. This includes, for example, the analysis of variations of market structure and network quality in specific cities.

[12] Body of European Regulators for Electronic Communications (BEREC)

[13] The HHI is commonly defined as: $HHI = \sum_{i=1}^{n}(s_i)^2$where s_i refers to the market share of firm i in percent.

Country	2011	2012	2013	2014	2015	2016	Mergers & Acquisitions or Market Entrants
Austria	4	4	3	3	3	3	H3G Austria/Orange AT
Croatia	3	3	3	3	3	3	-
Czech Republic	3	3	3	3	3	3	-
France	3	4	4	4	4	4	Free Mobile (Iliad)
Germany	4	4	4	4	3	3	Telefonica DE/E-Plus
Hungary	3	3	3	3	3	3	-
Ireland	4	4	4	4	3	3	H3G Ireland/Telefonica IE
Italy	4	4	4	4	4	4	-
Netherlands	4	4	4	4	4	4	-
Norway	3	3	3	3*	3	3	Tele2/Telia Sonera, Ice.net
Romania	4	4	4	4	4	4	-
Slovakia	3	3	3	3	4	4	4KA (Swan)
Spain	4	4	4	4	4	4	-
United Kingdom	4	4	4	4	4	4	-

Table 4.1: *Number of competitors by country and year. For brevity the table is aggregated on a yearly level, although the analysis is based on quarterly data. *The Tele2/Telia Sonera merger in 2014 included remedies which enabled the simultaneous market entry of Ice.net. Data source: company statements and market reports of regulation authorities.*

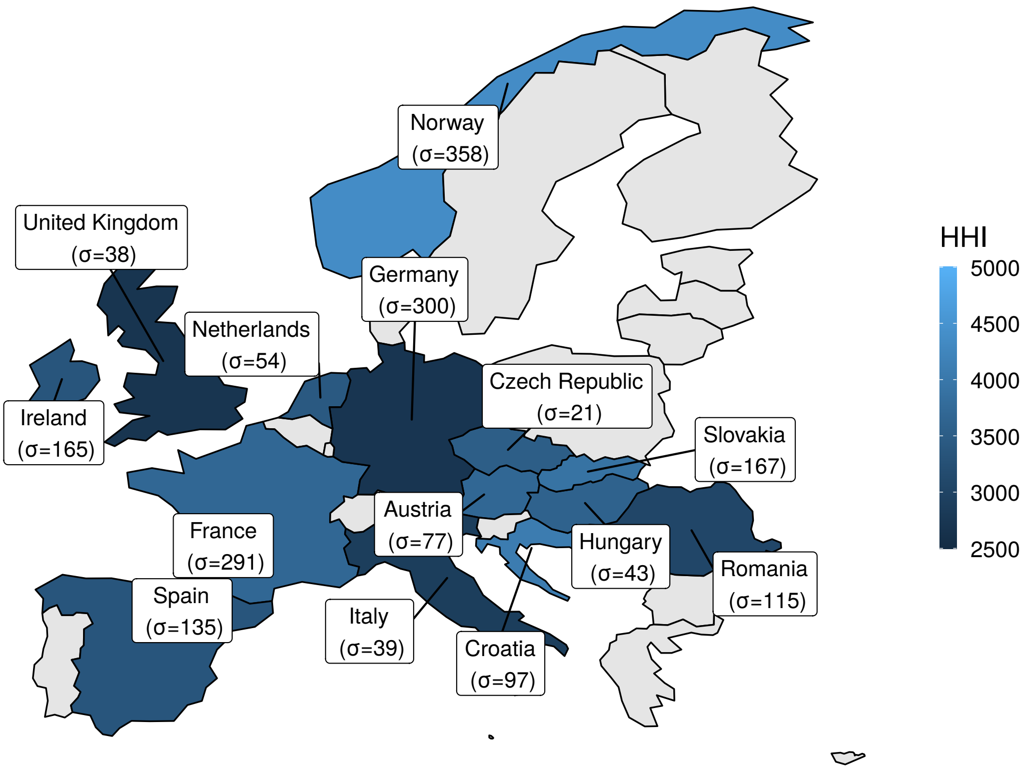

Figure 4.1: *HHI and standard deviation by country. The colors represent the HHI in Q1 2011 in each country while The standard deviation of the HHI during the period of analysis is denoted in brackets. Own computation and illustration, data source: company statements and market reports of regulation authorities.*

During the period of analysis, four M&A's and three market entries occurred in the observed markets (Table 4.1). Generally, the number of competitors in the observed markets is rather low and ranges only between three or four players. Interestingly, it seems that smaller markets (e.g., Norway, Croatia, Slovakia) mostly consist of three players, while larger markets (e.g., Spain, United Kingdom, Italy) mostly consist of four players. A more differentiated picture of the market structure can be observed in Figure 4.1 which displays the HHI by country. This accounts for both the number of players in the market and the asymmetry of their market shares. Precisely, each country is colored with the HHI in Q1 2011, while the standard deviation between Q1 2011 and Q1 2016 is shown in brackets with σ. It can be observed that the market concentration does not necessarily coincide with the market size. Thus, variations in market concentration are driven not only by changes in the number of players but also due to the gains and losses of market shares. This becomes apparent in countries like Spain, Croatia, and Romania, where significant changes in the standard deviation are observed, despite the number of market players did not change. Furthermore, it can be observed that overall market concentration is fairly high as the HHI ranges approximately between 2500 and 5000. For example a merger in the European Union is subject to a closer analysis as soon as the HHI is larger than 2000 and changes due to the merger by more than 150 (European Commission 2004).

4G Spectrum Auctions (800 Mhz)	
2010	Germany Netherlands.
2011	Italy France Spain.
2012	Czech Republic Romania Ireland.
2013	Austria Croatia Norway Slovakia UK.
2014	Hungary.

4G Spectrum Auctions (2600 Mhz)	
before	Norway.
2010	Germany Netherlands Austria.
2011	Italy France Spain.
2012	Czech Republic Romania.
2013	Slovakia UK.

Table 4.2: *Year of Spectrum Auction by Frequency and Country. Sources: European Commission (2017), European Communication Office (2020)*

An important lever for the upgrade of mobile networks is the auctioning of 4G spectrum. Table 4.2 shows the date of spectrum auctions by frequency and country. Typically, spectrum for 4G has been auctioned within the range of 800 MHz and 2600 MHz. Though there are also exceptions like Ireland where in 2012 spectrum was also auctioned for 900 and 1800 MHz bands (COMREG 2012). Generally, higher frequencies have the advantage of higher transmission capacities while lower frequencies have the advantage of higher transmission distances.[14] Typically, both are used by MNOs to best adapt to the different needs, of mobile users, for instance in rural and urban areas. Although, the timing of spectrum auctions is quite heterogeneous among different countries, most of the auctions took place between 2010 and 2013. This implies that most MNOs were also able to roll out the 4G technology from 2014 onwards.

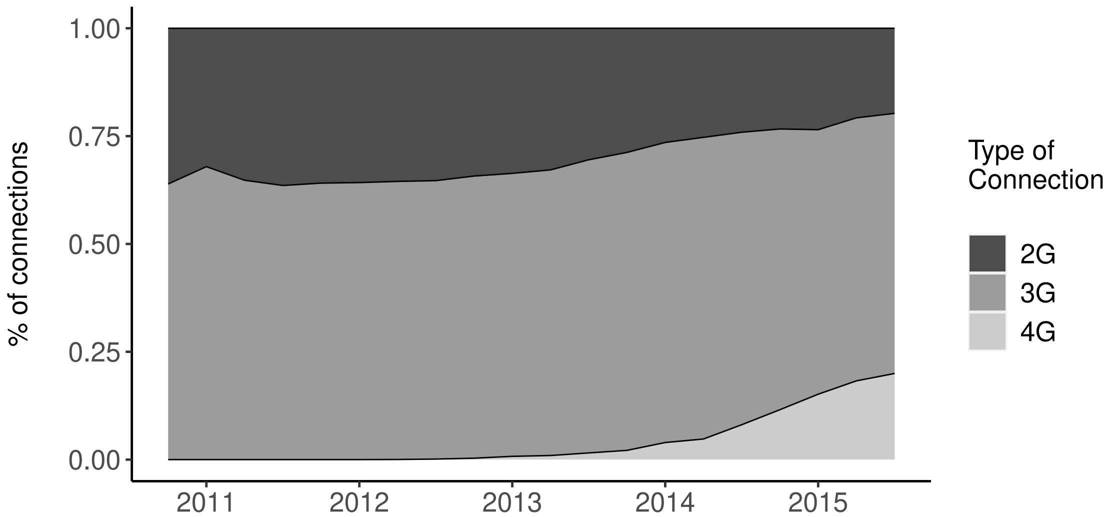

Figure 4.2: *Share of Connections for Different Technology Types between Q1 2011 and Q1 2016. Own calculation and illustration, data: Device Analyzer.*

Figure 4.2 displays the share of connections in the dataset by technology during the period of analysis. The share of connections is dominated by the 3G technology which gained shares until mid-2013. From there on it lost shares due to the introduction of 4G technology. This experienced a strong growth in the last quarter of the observation period. Interestingly, this coincides with the time when most MNOs had acquired a spectrum license to roll out 4G. Otherwise, this would require us to specifically account for these differences in the level playing field in the empirical analysis. 2G connections account for a significant share in 2011 but consistently loses importance

[14]For details on the functionality of mobile telecommunication networks see, for example, Gruber (2005) chapter 2.2.

over time. All in all, the market development of all technologies is fairly dynamic over time but also interdependent. This is not surprising, given that the roll-out of new mobile technologies imply a replacement or upgrade of the existing technology of mobile phone towers. However, this suggests for further analysis that it might be misleading to focus only on the development of one specific technology. Instead, these interdependencies need to be explicitly considered in the empirical model.

4.4 Empirical Framework

Our analysis is based on the empirical framework by Genakos, Valletti, and Verboven (2018). We adapt this for our analysis by considering different measures for network quality instead of capital expenditures as a dependent variable. Further extensions include different control variables which are relevant for the specific scope and time frame of the analysis. Given that Motta and Tarantino (2017) and Federico et al. (2018) observe different effects of mergers on investments at the firm and market level, both are studied in the analysis of mobile network quality.

At the firm level we assume that network quality of MNO i in country c at time t is specified by the following function:

$$network\,Quality_{cit} \quad = \quad \beta_1 N_{ct} + \beta_2 entry_{ci} + \beta_3 X_{cit} + \beta_4 \boldsymbol{\lambda}_c + \beta_5 \boldsymbol{T}_t + \epsilon_{cit}$$

At the market level we assume that the network quality of country c at time t is specified by the following function:

$$network\,Quality_{ct} \quad = \quad \beta_1 N_{ct} + \beta_2 X_{ct} + \beta_4 \boldsymbol{\lambda}_c + \beta_5 \boldsymbol{T}_t + \epsilon_{ct}$$

In the equations N_{ct} denotes the number of MNOs in the market, $entry_{ci}$ their entry position in the market and X_{cit} denotes a vector of further market characteristics and regulatory variables, $\boldsymbol{\lambda}_c$ and $\boldsymbol{T}_t$ include, respectively, country and time-specific effects while ϵ_{cit} and ϵ_{ct} denote the idiosyncratic error terms respectively. For the analysis at market level, firm-specific variables are averaged and weighted with the market share of each MNO in each market and time period.

4.4.1 Dependent Variables

An important consideration in this paper is the specification of the dependent variable with different quality measures. In the analysis these have been aggregated at the national level as parameters on market structure and regulation typically vary at the national level as well. This includes, for example, the assignment of spectrum licenses or the regulation of mobile termination rates. Moreover, competition in the mobile market typically takes place along national borders. Analyzing mobile network quality in a few specific cities therefore provides limited insights. Besides not being representative, it ignores mobile network quality in rural areas, which can significantly differ from cities. Analyzing household coverage takes into consideration one important location but misses out several other important ones. This includes, for example, coverage in businesses and commercial areas, along transportation routes or on public transport. Mobile coverage here is relevant for employees who work en route but also services like navigation, logistics tracking or emergency calls. Additionally, it seems unlikely that there is sufficient variation over time across MNOs in coverage of households. For one, coverage of their households is likely a major determinant in the consumption decision of consumers. For another spectrum licenses typically include various regulations regarding the roll-out. For instance in the 5G spectrum auction in Germany these included regulations on households coverage by certain dates. Failure to comply with these are subject to punishment and may ultimately lead to a shutdown of their mobile network (Bundesnetzagentur 2018). Therefore, it is not surprising to observe little variation across MNOs regarding the roll-out of household coverage.

Specifying mobile network quality with the number of antennas is lacking one important information, namely mobile coverage. Given that this is subject to various influences, it is difficult to solely infer this from the absolute number of antennas. First, coverage of mobile antennas depends on its cellular frequency. Lower frequencies have a higher transmission distance while higher frequencies have a higher transmission capacity. Second, the transmission of signals depends on the surrounding topology and confounders like wifi signals. Third, a mobile antenna allows only a limited number of mobile users to connect. Therefore, a mobile user may have no coverage, despite being in range of a mobile antenna. A thorough analysis would need data on all these influences at a local level over time and account for this, to compare the quality of different mobile networks based on the number of mobile antennas. This seems hardly feasible. Instead, this analysis is based on mobile connections which are gathered at all kinds of locations during real-world mobile usage.[15]

Similar to the assignment of mobile spectrum, which is auctioned for each generation of mobile technology, the analysis in this paper is focused on different

[15] For details on the functionality of mobile telecommunication networks see, for example, Gruber (2005) chapter 2.2.

generations of mobile technology. This is subject to two major relevant developments as mentioned in the data description in Section 4.3: The share of 3G connections increases until the middle of the analysis and then loses importance due to the growth of 4G technologies. Focusing only on the development of 3G connections, misses the important addition of 4G in the last period. Focusing only on the 4G development in the recent period is likely to lack sufficient observations for the analysis. Additionally, pooling 3G and 4G connections into a share of mobile connections also avoids an endogeneity issue, as discussed in more detail after the introduction of the explanatory variables of the model. Consequently, both variables are pooled for the analysis which is also conducted in Faccio and Zingales (2019). However, this approach does not allow to distinguish between upgrades in present 3G networks and the roll-out of recent 4G networks which might be a drawback. Furthermore, the number of observed mobile cells in the data varies between countries and over time. Thus the share number of mobile connections by technology is used instead of their absolute number.

Next to the share of mobile cells with 3G or 4G connection, the analysis also considers different definitions of minimum speeds as well as the maximum mobile broadband speed. Given the widespread use of mobile technologies both in daily life and particularly in business applications it is interesting how market structure affects coverage with minimum needs. In contrast, the analysis of maximum speeds allows us to evaluate investments in the most recent mobile network technologies. To sum up, the share of 3G and 4G connections measures the overall distribution of connections with a recent standard, while the different minimum and maximum speeds measure the lower and upper tails of this distribution.

4.4.2 Main Explanatory Variables

One major explanatory variable of interest is the number of MNOs in each country. This accounts for the market concentration in each mobile market and may exhibit two opposing effects on the signal quality of mobile networks. A higher market concentration may lower the competitive pressure and thus exert a negative effect on mobile signal quality. For example, merging parties may have lower incentives to invest due to the market power effect (Federico et al. 2018). This effect may also dominate aggregate investments in the market (Motta and Tarantino 2017). However, the opposite might also be true and a higher market concentration in the market may actually increase mobile signal quality. For example, a higher market concentration may raise the incentives of firms to invest (Houngbonon and Jeanjean 2016, Jeanjean and Houngbonon 2017, Vives 2008, Bourreau and Jullien 2018) or induce them to invest more efficiently (Stoughton et al. 2017). In an alternative specification the HHI is used instead of the number of MNOs in the market. This accounts not only for market entries or mergers of MNOs, but also for asymmetries in the market shares.

The other major explanatory variable of interest is the entry position of an MNO into the mobile market. In the regression this variable is specified with dummy variables for the first, second, third, and fourth or later entrant. Using dummy variables instead of market shares has the advantage of allowing us to account for a possible non-linear effect on mobile network quality for different types of entry positions. This variable may have a positive effect on network quality, for example if market incumbents benefit from first-mover advantages (Jakopin and Klein 2012). Accordingly, incumbents may not only profit from synergies from their fixed network, their historically grown customer base may also give rise to economies of scale. These competitive advantages are of particular importance for the mobile market, as the acquisition of spectrum licenses and the roll-out of mobile networks require large investments by MNOs.[16]

However, late entrants may also have a competition advantage which may transmit into a better mobile network quality. Shankar et al. (1998) describe competitive advantages for late entrants in product innovation and product positioning. For example late entrants may have an advantage in product innovation as they can leapfrog legacy technology. Instead, they can purchase more recent and advanced mobile network technology than early entrants for similar investments. Given the rapid significant advances of mobile technology this is an important advantage. Late entrants may have an advantage in product positioning as they can take overlooked product positionings. So they can outperform previous entrants by tailoring mobile products closer to consumer preferences. This may also affect mobile network quality e.g., by raising overall network quality or by increasing coverage in a specific geographic area. Finally, Whalley and Curwen (2012) note that incumbents were more hesitant to upgrade their networks from 2G to 3G and relied instead on the advantage of a large customer base to compete. Thus the competitive first mover advantage of incumbents and their larger profits do not necessarily transmit into superior network quality. Instead, late entrants may have room in product positioning and can supply the superior network quality if this is demanded.

[16]For example, estimates by the European Parliament suggest that the roll-out of 5G networks in Europe will cost 500 billion € to meet the EU 2025 connectivity targets (European Parliament 2019). Thus it is not surprising that MNOs do not always meet these demanding investments requirements. For example, *Xfera* required six years, after its entry into the spanish market, to roll out their mobile network and had to renegotiate the terms of its spectrum license before it was finally able to launch their mobile network (TeliaSonera 2006).

4.4.3 Further Control Variables

One set of additional control variables are market characteristics. This includes the GDP per capita which accounts for the income of consumers. MNOs might be more willing to invest in recent mobile networks if consumers can more likely afford the costs for subscriptions and recent handsets. The latter is relevant for the roll-out of 4G networks as it requires compatible handsets by mobile users. Another important market characteristic is market size. Larger markets may not only provide larger economies of scale (Jeanjean and Houngbonon 2017) but also higher incentives to invest (Vives 2008) and may thus raise mobile network quality. Finally, the degree of urbanization is an important market characteristic which affects the demand and supply of mobile services. Though, there might be gaps in the provision of mobile services in urban and rural areas (Prieger 2013), this is not necessarily a shortcoming of competition. Given the substantial fixed costs for mobile networks, it might be simply inefficient to offer the best mobile connectivity in areas with limited demand. In the estimation we proxy for urbanization with the mean number of wifi access points across mobile cells. Today, wifi networks are common not only in most households and enterprises to access the fixed network. They also occur in other areas of urban life such as bars, cafés or even on public transport. Among the mentioned places might also be locations which offer public wifi. So places with a higher number of wifi access points may indicate a higher degree of urban density but also substitution opportunities for mobile networks. However, given that this variable also captures wifi networks on different floors of surrounding buildings, it is most likely driven by wifi networks from local residents.

Another set of additional control variables account for regulations in the mobile market and which may also affect investments in mobile networks. In the EU mobile termination rates are subject to regulation at the national level. These interconnection fees have to be paid by MNO A if a call from his mobile network terminates in the mobile network of MNO B. As these fees give rise to the exploitation of market power they are regulated. Albeit termination rates have been reduced in the past, significant differences between countries and operators remain. Studies suggest that reductions in termination rates can significantly affect price levels. Interestingly, these regulations may either lower prices (e.g., Hawthorne 2018, Grzybowski 2008) but under certain circumstances they may also increase prices, which is known as the waterbed effect (Genakos and Valletti 2011). However, in turn this may also affect the profitability of mobile services and thus investments in mobile network quality.

At the European level the regulation of mobile telecommunication services includes roaming fees. These include price caps for wholesale- and retail data, incoming and outgoing voice calls, and text messages. According to the mobile industry these price caps are likely to lower profitability and investments in mobile networks (GSMA 2012). After the introduction of price caps several reductions were introduced and, during the period of analysis, price caps nearly halved. Thus, it will be interesting to investigate the effect of the different roaming price caps on mobile network quality in detail.

Providing wholesale access for mobile virtual network operators (MVNO) is an important remedy in mobile mergers in the EU.[17] Given that MVNOs do not own any spectrum themselves, their wholesale access to spectrum may be affected by competition between MNOs in the upstream market. Thus it will be interesting to see whether systematic differences in the network quality between MVNOs and MNOs are present. In the specification we account for these differences by adding a dummy variable in the regression and considering data from 16 MVNOs additionally.

4.4.4 Potential Endogeneity Concerns

One endogeneity threat may arise from the specification of the dependent variable. During the analysis MNOs face the simultaneous decision to deploy and upgrade 2G, 3G, and 4G antennas. Consequently, the analysis needs to account for the substitution between different technologies. Obviously, one opportunity to address this is the use of instrumental variables. However, a relevant and exogenous instrument in this case needs to meet several requirements: First, an instrument is needed for each of these technologies at each of the 49 MNOs, but it is only allowed to influence each combination separately. Second, this type of instrument needs to be readily available across 49 MNOs. Third, it needs to fluctuate over time, otherwise this would rule out the use of panel data methods in further analysis. Finally, it also needs to be observable by the econometrician. In practice it seems hardly feasible to find such an instrument. Instead, this paper proceeds with a different approach and addresses the endogeneity by adding the endogenous variables to the dependent variable. This can be done by pooling the share of 3G and 4G technologies and using it as a dependent variables. Aside from that it is motivated by the heterogeneous development of the technologies over time in the data, it allows us to circumvent the endogeneity problem.[18] The use of the other dependent variables, namely the share of technologies which exceed different minimum speeds as well as the observed maximum speeds, follows a similar rationale.

[17] This includes, for example, the H3G Austria/Orange AT merger in 2012 as well as the Telefónica Germany/E-Plus merger in 2014.

[18] See also the specification of the main variables in this section.

Given that the included control variables in the estimation are determined in market equilibrium, their exogeneity needs to be discussed. One of these variables is the number of market players. Typically, papers in industrial organization consider market entry and exit as endogenous. For example, a lower product quality in the market may raise the incentive for a market entrant to cover the high quality product niche. However, it cannot be ignored that the mobile market differs from other markets with regard to the entry and exit barriers. (See also the discussion in Genakos, Valletti, and Verboven 2018, Houngbonon and Jeanjean 2016.) A legal entry barrier arises from the allocation of spectrum which is limited, and only auctioned once or twice in a decade. The availability depends on the institutional endowments and license terms of a country. Acquiring a spectrum license is fairly costly and adds to the high fixed costs for the roll-out of the mobile network. These high fixed costs are likely sunk which can be considered as an economic entry barrier (Baumol and Willig 1981). Exiting the mobile market by M&A is restricted by merger control. As the number of market players in the considered markets ranges between three or four players, M&A are under subject to closer analysis by the European Competition Commission.[19] To sum up, it is acknowledged that entry and exit in the mobile market is unlikely to be endogenous. Nonetheless, it cannot be ruled out that endogeneity is present which may potentially distort the regression results. Consequently, the estimation strategy is as follows: To raise the robustness of the estimation as much as possible the main regression results are conducted with instrumental variables. However, as part of the robustness checks these estimates are also compared to an estimation without instrumental variable. This allows us to contrast the presence and magnitude of a potential endogeneity bias with the efficiency cost of an instrumental variable estimation.

Another source of endogeneity in the market concentration measures arises from the HHI, as it is also based on market shares. For example, an inferior mobile network quality may increase the churn rate and thus affect market shares. In the empirical strategy this is addressed with instrumental variables. Henceforth, we follow the theoretical foundation of two instruments. Accompanying statistical tests of the relevance and endogeneity of these instruments are reported with the regression results in Section 4.5.

One type of instrument for the market concentration measures is based on multimarket contacts as these may increase the incentive for collusive behavior. According to Edwards (1955) firms, which meet repeatedly again in different markets, have an incentive to "live and let live [...] in the hope of reciprocal recognition."

[19] See also Table 4.1 in Section 4.3.

Otherwise an "unmitigated competitive attack [...] at one point of contact" may lead to "retaliatory action [...] at many other points of contact" and "may call for conversion of the warfare into total war." Bernheim and Whinston (1990) show in a seminal paper that multimarket contacts are likely to encourage collusive behavior. Generally, the oligopolistic market structure, the transparent pricing by firms, and consumption decisions by consumers make the mobile market already prone to collusive behavior (Choi and Gerlach 2014). Thus, it is not surprising that Parker and Roeller (1997) confirm, that multimarket contacts facilitate collusive behavior for the mobile market in the US.

The mobile market in the EU is considered highly fragmented, as markets are typically defined along national borders. But in various cases MNOs in these markets are not independent firms, but belong to large multinationals. In other words, competition actually takes place between a smaller number of multinationals which repeatedly meet in different markets. In the analysis, 49 different MNOs from 14 countries are observed, but only 17 independent firms. However, the presence in other European markets is not equally distributed across these firms. For example, while Vodafone and Telekom are present in nearly half of the European mobile markets, others are only present in one market such as the Irish Meteor. Unsurprisingly, various multimarket contacts arise between these large multinationals which meet repeatedly again: For example in Germany and the Czech Republic (Vodafone, Telefonica, Deutsche Telekom) in Austria, Romania, and Slovakia (Orange, Deutsche Telekom) or in Slovakia and Spain (Orange, Telefonica). Given that the observed mobile markets consists of only three or four players, multimarket contacts likely facilitate collusive behavior here. (Recent) market entries in the European mobile market seem to confirm this. Market entries, which naturally increase the competitive pressure in the market, were in various cases conducted from market outsiders: For example, *Hutchison 3* which entered various markets in the EU, 4KA (Swan) in Slovakia, Free Mobile (Iliad) in France, Ice.net in Norway or 1&1 Drillisch in Germany. In the estimation the instrument considers the variation of multimarket contacts over time across different MNOs and markets.[20] At the same time it is unlikely that multimarket contacts affect mobile network quality directly. Accounting for a possible U-shaped relationship between multimarket contacts and conduct (see also Baum and Korn 1999), a quadratic term of the instrument is included. Further, to raise the robustness of the regression results, the estimation is also conducted with another instrument, besides multimarket contacts, to confirm the regression results and the validity of the instruments.

[20]See also the Data Description in Section 4.3.

Another type of instrument for the competition measures is based on the asymmetry of mobile termination rates. Adjustments of these by regulators differ in the timing and magnitude between countries and MNOs while the reasons for these changes are rooted in legal and institutional circumstances (Genakos and Valletti 2011). Peitz (2005) shows that regulation in favor of smaller MNOs fosters competition. Allowing these smaller MNOs to charge higher mobile termination rates provides them with a competitive advantage which may allow them to achieve a more dominant market position. The asymmetries in market sizes usually arise due to late entry or long and persistent size differences between MNOs (Houngbonon and Jeanjean 2016). Besides from the regression also including control variables for mobile termination, there is also no obvious reason why asymmetries in these should directly affect mobile network quality. Hence, asymmetries of mobile termination rates are likely relevantly exogenous and may serve as an instrument in the analysis.

Besides the competition measures an endogeneity problem may also arise from market size. For example, a higher mobile network quality may also increase the incentives for consumers to subscribe and this may augment the market of mobile users. To address this issue, the market population is used in the estimation as a measure for market size (similar to Genakos, Valletti, and Verboven 2018). Given the widespread use of mobile phones, this is closely related. At the same time, population is unrelated to demand parameters, as noted before in Houngbonon and Jeanjean (2016).

Finally, the data from different countries may give rise to an endogeneity bias due to unobserved heterogeneity: As noticed in the data description in Section 4.3, 4G did not become relevant in the data before most countries had already auctioned 4G spectrum. Nonetheless, differences in the auctioning of 4G may still affect the preparation time for the roll-out. This is accounted for with country fixed effects. Furthermore, country specific differences may arise in the topology. Naturally, this may also affect the costs for building and maintaining a mobile network and may thus affect the mobile network quality. Moreover, there might be country-specific regulations like the ban of handset subsidies in some countries. This may affect the upgrade to 4G handsets which is relevant for the roll-out of 4G services. Finally, there might be persistent country- specific differences in consumer preferences. The estimation accounts for this unobserved heterogeneity with fixed effects at country level. Furthermore, time dummies account for the rapid and potentially non-linear technological development of mobile technology.

4.5 Empirical Results

This section presents the regression results, first at the firm level and then at the market level. All specifications have been estimated with country and year fixed effects and instrumental variables. The reported standard errors are robust to heteroscedasticity and clustered on the operator-country level. Overall, it can be observed that the sign, significance, and magnitude of the main variables of interest are fairly similar across most of the different specifications. Precisely, a lower number of MNOs or a higher market concentration raises the mobile network quality across all quality measures. Further, late entrants provide a higher share of connections to 3G and 4G as well as different minimum speeds. Market incumbents seem to excel with higher maximum speeds.

Table 4.3 presents the estimation results at the firm level with different types of control variables. Specifications 1) and 2) present the baseline setup of the analysis with different competition measures, the number of MNOs and the HHI. Accordingly, raising competition with a market entry of an MNO lowers the share of mobile cells with 3G or 4G connection by -5.5 percentage points. Accounting also for the asymmetry of market shares, a similar effect is observed for a reduction of market concentration by $\Delta HHI =$ -250. Interestingly, the regression results indicate that late entrants provide a significantly higher share of 3G or 4G connection compared to the market incumbent. This share is 3 percentage points higher for the 2nd entrant, 4.6 percentage points for the 3rd entrant and with 10 percentage points it is highest for the 4th or later market entrants. This findings suggest that the usage of 2G antennas is still very present for market incumbents. Urban density is mostly highly significant, but exhibits only a small effect on the dependent variable. Consumer income is mostly highly significant and also a major driver of the regression results. Specifications 3), 4) and 5) present regression results for extensions of the baseline setup with different control variables. It can be observed that neither market size, price caps for different roaming services nor the dummy for MVNOs are significant. In the table the reported price caps refer to data roaming, while voice calls refer to outgoing voice calls. A similar effect is observed for roaming price caps on retail data and incoming voice calls, which are not reported for brevity.

Table 4.4 presents the estimation results for the baseline setup at the firm level for different quality measures. Namely, the share of different minimum speeds as well as the observed maximum speed. The results confirm the observations from table 4.3: The HHI has a positive effect on the different quality measures for mobile network quality and is mostly highly significant. Similarly, a better coverage with certain minimum speeds can be observed for late entrants. Higher maximum speeds

	Firm Level				
	Share of 3G or 4G connections				
	(1)	(2)	(3)	(4)	(5)
No. of Competitors	-0.055^{**}		-0.052^{*}	-0.052^{*}	-0.080^{***}
	(0.027)		(0.028)	(0.028)	(0.027)
HHI		0.0002^{**}			
		(0.0001)			
2nd Entrant	0.030^{***}	0.029^{***}	0.030^{***}	0.031^{***}	
	(0.010)	(0.010)	(0.009)	(0.009)	
3rd Entrant	0.046^{***}	0.046^{***}	0.046^{***}	0.047^{***}	
	(0.012)	(0.012)	(0.012)	(0.012)	
4th Entrant+	0.100^{***}	0.100^{***}	0.101^{***}	0.101^{***}	
	(0.013)	(0.013)	(0.013)	(0.013)	
Mobile Termination Rates	-0.007	-0.007	-0.007^{*}	-0.008^{*}	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Urban Density	0.004^{**}	0.005^{**}	0.004^{**}	0.004^{**}	0.005^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log(GDP per capita)	0.205^{***}	0.223^{***}	0.210^{***}	0.205^{**}	0.191^{***}
	(0.075)	(0.075)	(0.075)	(0.080)	(0.074)
log(Marketsize)			0.706	0.734	0.974
			(1.054)	(1.084)	(1.020)
Data Roaming Cap				0.001	
				(0.002)	
Voice Call Roaming Cap				-0.0005	
				(0.006)	
Text Roaming Cap				-1.136	
				(2.001)	
MVNO					0.005
					(0.015)
Instrument Variables	mmc	mmc	mmc	mmc	mmc
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
F-Statistic	33.80^{***}	32.38^{***}	34.43^{***}	31.63^{***}	32.11^{***}
Observations	705	705	705	705	812
Adjusted R^2	0.394	0.353	0.394	0.392	0.337

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Heteroskedasticity and Cluster Robust Standard Errors

Table 4.3: *Main Regression Results at the Firm Level with Different Control Variables.*

	Firm Level			
	Share > 1MBps	Share > 2MBps	Share > 3MBps	log(Max. speed)
	(1)	(2)	(3)	(4)
HHI	0.0004***	0.0004***	0.0004***	0.001*
	(0.0001)	(0.0001)	(0.0001)	(0.0004)
2nd Entrant	0.002	−0.008	−0.019	−0.090**
	(0.014)	(0.013)	(0.012)	(0.039)
3rd Entrant	0.056***	0.037**	0.007	−0.284***
	(0.016)	(0.015)	(0.013)	(0.062)
4th Entrant+	0.075***	0.061***	0.040***	−0.109***
	(0.018)	(0.017)	(0.015)	(0.042)
Mobile Termination Rates	−0.019***	−0.019***	−0.017***	−0.098***
	(0.006)	(0.005)	(0.004)	(0.014)
Mean Urban Density	0.002	0.004	0.005*	0.013**
	(0.003)	(0.003)	(0.003)	(0.006)
log(GDP per capita)	0.283***	0.261***	0.192**	1.994***
	(0.099)	(0.093)	(0.084)	(0.287)
Instrument Variable	mmc	mmc	mmc	mmc
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
F-Statistic	28.95***	31.95***	42.40***	168.99***
Observations	705	705	705	705
Adjusted R^2	0.343	0.372	0.462	0.734

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity and Cluster Robust Standard Errors

Table 4.4: *Alternative Regression Results at the Firm Level for Different Measures of Mobile Network Quality.*

Table 4.5: *Main Regression Results at the Market Level with Different Control Variables.*

	Market Level			
	Share of 3G or 4G connections			
	(1)	(2)	(3)	(4)
No. of Competitors	−0.070***		−0.066***	−0.064***
	(0.011)		(0.011)	(0.011)
HHI		0.0001***		
		(0.00001)		
Mean Mobile Termination Rates	−0.007	−0.0001	−0.006	−0.004
	(0.006)	(0.007)	(0.006)	(0.007)
Mean Urban Density	0.007	0.021*	0.011	0.011
	(0.007)	(0.011)	(0.009)	(0.009)
log(GDP per capita)	0.156***	0.161***	0.154***	0.134***
	(0.038)	(0.043)	(0.038)	(0.046)
log(Marketsize)		−0.746	−0.327	−0.446
		(0.714)	(0.540)	(0.583)
Data Roaming Cap				0.0003
				(0.0004)
Voice Call Roaming Cap				−0.001
				(0.002)
Text Roaming Cap				−0.071
				(0.577)
Instrument Variables	mmc	mmc	mmc	mmc
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
F-Statistic	247.67***	301.89***	490.77***	86.19***
Observations	128	128	128	128
Adjusted R^2	0.828	0.745	0.826	0.821

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity and Cluster Robust Standard Errors

	Market Level			
	Share > 1MBps	Share > 2MBps	Share > 3MBps	log(Max. speed)
	(1)	(2)	(3)	(4)
HHI	0.0001**	0.0001**	0.0001**	0.001***
	(0.00003)	(0.00003)	(0.00003)	(0.0003)
Mobile Termination Rates	−0.005	−0.003	−0.004	−0.355***
	(0.006)	(0.006)	(0.006)	(0.108)
Urban Density	0.009	0.011	0.008	−0.005
	(0.010)	(0.010)	(0.010)	(0.112)
log(GDP per capita)	0.174***	0.172***	0.175***	3.577***
	(0.043)	(0.045)	(0.049)	(0.650)
Instrument Variable	mmc	mmc	mmc	mmc
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
F-Statistic	442.39***	644.44***	411.73***	141.25***
Observations	128	128	128	128
Adjusted R^2	0.787	0.808	0.823	0.869
Note:				*p<0.1; **p<0.05; ***p<0.01 Heteroskedasticity and Cluster Robust Standard Errors

Table 4.6: *Main Regression Results at the Market level with Different Control Variables.*

are provided by market incumbents. Furthermore, a highly significant and negative effect of mobile termination rates can be observed on all considered speed measures.

Tables 4.5 and 4.6 present estimation results with different control variables and for different quality measures but at the market level. Due to the aggregation of the observations at the market level, the number of observations naturally declines, which may principally also affect the significance of the estimates. Nonetheless, the results in both tables at market level confirm the results from previous estimations at the firm level. A higher number of MNOs or similarly a lower market concentration lower the share of 3G and 4G connections as well as different minimum and maximum speeds. This is highly significant at the 5% or even 1% level, while the magnitude is similar across all specifications. Further, GDP per capita exhibits a positive effect on mobile signal quality as has been also observed at the firm level. Higher mobile termination rates have a negative and highly significant effect on the provided maximum speeds.

One important finding in the regression results is that a higher market concentration raises mobile network quality. This includes both the share of 3G and 4G connectivity as well as different minimum and maximum speeds. This is in line with previous studies which find that a higher market concentration raises investments by MNO in the mobile telecommunication market (Jeanjean and Houngbonon 2017, Houngbonon and Jeanjean 2016, Genakos, Valletti, and Verboven 2018).[21] This paper confirms that these higher investments also transmit into a higher mobile network quality both at the firm and the market level and thus benefit consumers. More generally, this is another piece of evidence that competition and regulation authorities might face a potential trade-off. Given that there is strong evidence in the price-concentration literature, that a lower market concentration lowers prices, this might be traded-off with a lower mobile network quality.

So, how do the results connect to the theoretical findings by Motta and Tarantino (2017) and Federico et al. (2018) that mergers only increase investments at the market level if efficiency gains are present? One explanation might be rooted in merger control. Given the high market concentration in the observed markets, with only three or four players, mergers are under the close supervision of the European Competition Commission. Mergers are more likely to get approved if the parties can convincingly demonstrate that the merger allows the realization of merger efficiencies. For example these may arise from complementarities in spectrum licenses, in the mobile network infrastructure or a better load balancing of the mobile network capacity. The regression results do not necessarily contradict the findings in the theoretical literature, they may reflect both. So the observed mobile network quality may haven risen due to the realization of merger efficiencies. Genakos, Valletti, and Verboven (2018) note that these may also explain why a higher market concentration raises investments in their regression results at the firm level, but not at the market level. Another explanation could be related to the efficiency of investments. (Stoughton et al. 2017) find that a lower market concentration may also lower the efficiency of investments. So, the rise in mobile network quality is due to the more efficient allocation of investments in less concentrated markets. This may apply to variation from mergers and market entries, as the regression results are based on both. Finally, the theoretical literature is also not conclusive on this issue as various papers observe transmission channels which also lead to increases of investments in more concentrated markets (Bourreau and Jullien 2018, Schmutzler 2013, Vives 2008).

Another important finding in the regression results is related to the market entry position of MNOs. Late entrants provide a significantly higher share of connections to 3G or 4G as well as a higher share of connections to certain minimum speeds. This might be driven by different influences. First, late market entrants´ have an incentive to compete aggressively. As noted in different mergers by the European Competition Commission, late entrants in particular face competitive pressure to

[21] Genakos, Valletti, and Verboven (2018) only observe this effect at the firm level.

attract new customers as they cannot rely on an existing customer base to recoup the high upfront investments.[22] New customers can be attracted by lower prices, more advertisement, but also a higher mobile network quality. Second, as noted in Shankar et al. (1998) late entrants have an advantage in product innovation and product positioning. So MNOs can leapfrog legacy mobile network technology and start directly with the roll-out of state-of-the-art mobile networks. Here, they may profit from strong cost reductions due to the rapid development of ICT technology, but also save integration costs as they do not have to account for incompatibilities with their existing mobile network. Moreover, they may also use their technological advantage and use this as a product niche. For example, Hutchison 3 used its brand name to market its 3G network at market entry in various countries.[23] Third, given the high upfront costs in the mobile market, market entrants typically belong to large multinationals. This includes, for example, the market entry of Hutchison 3 in several European countries or the joint venture 'Everything Everywhere' owned by Orange and Deutsche Telekom in the United Kingdom. Finally, incumbents have a higher share of connections with 2G, but also higher maximum networks speeds. So it seems that incumbents are investing in recent 4G technology. But it seems that the hesitation to upgrade to 3G, as mentioned by Whalley and Curwen (2012), may still be persistent in the data.

Aside from the main variables of interest, there are also different interesting findings with regard to the control variables. One of these applies to the market size. According to Vives (2008) this raises investments, while Berry and Waldfogel (2010) find this empirically in an industry with high fixed costs. An explanation might be rooted in the mobile penetration rate, which is already high in the observed countries. So, the observed variation might not be sufficient during the period of analysis and this may render the regression results insignificant. But this is also in line with Genakos, Valletti, and Verboven (2018) who do not find a relevant effect of this variable on market investments alike. Another, notable result is the insignificance of the different price caps for roaming on mobile network quality. According to claims by the industry GSMA (2012), these regulations were also risking the quality of mobile networks. This could not be confirmed in the regression results. Tough it cannot be ruled out that the industry has responded to this issue on the price level: For example by raising prices or postponing price reductions or improvements of mobile tariffs. Further, partially it is also observed that lower mobile termination rates raise the mobile network quality. So this partial evidence complements the

[22] See, for example, the merger of Hutchison 3G Austria / Orange AT (2012) or T- Mobile Austria/Tele.ring (2006).

[23] Similarly, Tele2 marketed itself at entry into the Dutch market as '4G-only' operator.

literature which documents that the regulation of termination rates lowers prices (e.g., Hawthorne 2018, Grzybowski 2008.) Finally, the share of 3G and 4G connections does not significantly differ between MVNOs and MNO. So there is no indication that the current state of competition between MNOs in the upstream negatively affects the access of MVNOs to mobile networks.

To ensure the robustness of the regression results various preliminary considerations have been taken in the empirical strategy, as previously mentioned: The analysis is based on European countries, as these are subject to relatively homogeneous economic, regulatory, geographical, and technical conditions. The data is gathered from real-world mobile phone usage and accounts for all types of situations which typically arise for mobile users. The collection of the data is done through a general purpose app, which makes it unlikely that the data is subject to a sample selection bias which affects the estimation results. In the estimation various control variables account for country and time-specific influences and additionally for different economic, geographic, and regulatory confounders. Furthermore, instrumental variables are used to account for a possible endogeneity bias from the competition variables.

Different robustness checks were made following the estimation. First, the main estimation results can be confirmed in regressions with different competition parameters, control variables, dependent variables, both at the firm and the market level. Second, the estimates are significant and mostly highly significant while the magnitude of the effects is within a similar range across all specifications. Third, the results do not change when a linear or quadratic time trend instead of year dummies or quarterly dummies are added. Fourth, we test the hypothesis that market incumbents provide a 2G connection in locations (e.g. remote areas) where other MNOs do not provide coverage at all. This would provide a further explanation for why the share of 2G connections is higher for market incumbents than late entrants. This can be tested by running a regression on the share of connections without signal with the same explanatory variables as in the main model (Table 4.3). However, not any of the considered variables is statistically significant and the hypothesis is rejected.Finally, given that Schmutzler (2013) and Aghion, Bloom, et al. (2005) observe a non-linear relationship between competition and investments, it would be interesting to test this. But, the data only includes markets with three or four players. Thus there is too little variation to test a non-linear relationship between the number of market players and mobile network quality. However, most European mobile markets and also larger mobile markets like in the US, China or Japan consist of three or four players. Thus testing a non-linear effect has limited practical relevance.

A number of robustness checks have been conducted with regard to the instrumental variables. An estimation bias due to weak instruments (see Bound et al. 1995) is ruled out: First-stage regression results indicate a strong power as both types of instruments are very significant at the 1% level. This is complemented by the F-statistic of the excluded instruments which is larger than 10. Similar regression results are obtained with two types of instruments. Table 4.11 in the appendix reports the regression results with instruments using the difference in mobile termination rates in specification 3) and multi market contacts in specification 4). Further, the Sargan–Hansen test for over-identifying restrictions, confirms these results as we cannot reject the null hypothesis that both variables are exogenous (p=0.35). Finally, specifications 1) and 2) in the table display comparisons of fixed estimation results with and without instruments for the number of market players. It can be observed that both estimates differ (without instruments: -0.047, with instruments: -0.055) while the standard error is also larger in the estimation with instrumental variables.[24] So in fact, the estimators barely differ and the endogeneity bias is likely very small. This suggests that the aforementioned arguments regarding the exogenous determination of market entry and exit in the mobile market are valid.

4.6 Conclusion

This paper analyzes how the market structure affects different measures of mobile network quality. The analysis is based on quarterly data from 49 MNOs from 14 European countries between 2011 and 2016. The quality measures are calculated based on 500 million measurements of mobile network quality. These are regressed against the market concentration and the market entry position while controlling for various confounding influences of economic and regulatory variables. The estimation is based on a fixed effects approach with instrumental variables to consider for various kinds of potential endogeneity threats. To the best of our knowledge this paper is among the first to provide this kind of analysis on the relationship between market structure and mobile network quality.

First, one main result of this paper suggests that a higher market concentration seems to improve the different measures for mobile network quality. Interestingly, this effect is observed both at the firm and also at the market level. Second, the other main result is that late entrants seem to provide a higher share of 3G and 4G

[24]The estimation with the instrumental variable is less precise, but still significant at the 5% level.

connections and connections with different minimum speeds than market incumbents. Market incumbents seem to provide higher maximum speeds instead. There are also different minor results. Third, it cannot not be confirmed that these different roaming price caps lower the mobile network quality. Fourth, there is partial evidence that that lower mobile termination rates seem to increase mobile network quality. Fifth, there seems to be no significant difference between the mobile network quality of MNOs and MVNOs. To ensure the robustness of our results, various checks are conducted. The results are confirmed for different measures for competition, control variables, measures for mobile network quality, as well as different sets of instrumental variables at the firm and market level.

More generally, the results of this paper would confirm the findings from the recent literature (Jeanjean and Houngbonon 2017, Houngbonon and Jeanjean 2016, Genakos, Valletti, and Verboven 2018) that suggests a higher market concentration increases investments. Given that there is considerable evidence in the price-concentration literature that a higher market concentration may raise prices, the results of this paper may imply that regulators face a potential trade-off: Either they aim for lower prices or for a higher mobile network quality. For the current wave of mergers in the mobile market, this may have potential implications. A reduction of market concentration may, depending on the specific market circumstances, increase mobile network quality at the cost of potentially higher market prices. For the ongoing or upcoming auctioning of 5G spectrum this may be relevant for the regulation of the spectrum license. A less strict regulation may raise the probability of market entry. This may yield lower mobile prices, but may come at the cost of a lower quality of 5G networks. The vice versa effects for prices and network quality may be observed for a stricter regulation. In any case decision makers in both merger cases and spectrum auctions need to carefully investigate the market-specific circumstances. In particular the current state of price levels and mobile network quality will be important so as to carefully balance the aforementioned effects.

Finally, the analysis of this paper is among the first on this topic and the results hold important implications for competition and regulation policy. However, the literature on this topic is still scant and more research is required given the strong implications merger decisions and spectrum auctions have on the mobile market. This may on the one hand focus on the link between investments and mobile network quality. It will be interesting to investigate in more detail what the underlying link between mobile network quality and capital expenditures is and what role do inefficiencies of investments play with regard to market concentration. On the other hand, further research will be particularly interesting for non-EU markets. The high market fragmentation, the importance of MVNOs and low investment levels make the EU distinct from other mobile telecommunication markets in several aspects (see also Bruegel 2015). It will be interesting to empirically investigate the relationship between market concentration and network quality both at the firm and market level for non-EU markets. Finally, it will be interesting to investigate whether a similar potential trade-off as discussed for the mobile telecommunication market is found for other markets, too. In particular this concerns markets where investments play a similar central role. However, an essential requirement for this might be that quality can be objectively quantified, which is not always the case.

Bibliography

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and Innovation: An Inverted-U Relationship. *The Quarterly Journal of Economics*, *120*(2), 701–728.

Aghion, P., & Tirole, J. (1994). The Management of Innovation. *The Quarterly Journal of Economics*, *109*(4), 1185–1209.

Arrow, K. (1962). Economic Welfare and the Allocation of Resources for Invention. *The Rate and Direction of Inventive Activity: Economic and Social Factors*, 609–626. Retrieved July 20, 2018, from http://www.nber.org/chapters/c2144

Ashenfelter, O. C., Hosken, D. S., & Weinberg, M. C. (2015). Efficiencies brewed: Pricing and consolidation in the us beer industry. *The RAND Journal of Economics*, *46*(2), 328–361.

Asplund, M., & Friberg, R. (2002). Food prices and market structure in sweden. *The Scandinavian Journal of Economics*, *104*(4), 547–566.

Bain, J. S. (1951). Relation of Profit Rate to Industry Concentration: American Manufacturing, 1936–1940. *The Quarterly Journal of Economics*, *65*(3), 293–324.

Baker, J., & Rubinfeld, D. (1999). Empirical methods in antitrust litigation: review and critique. *American Law and Economics Review*, *1*(1), 386–435.

Baum, J. A. C., & Korn, H. J. (1999). Dynamics of dyadic competitive interaction. *Strategic Management Journal*, *20*(3), 251–278.

Baumol, W. J., & Willig, R. D. (1981). Fixed costs, sunk costs, entry barriers, and sustainability of monopoly. *The Quarterly Journal of Economics*, *96*(3), 405–431.

Bernheim, B. D., & Whinston, M. D. (1990). Multimarket Contact and Collusive Behavior. *The RAND Journal of Economics*, *21*(1), 1–26.

Berry, S., & Waldfogel, J. (2010). Product quality and market size. *The Journal of Industrial Economics*, *58*(1), 1–31.

Blundell, R., Griffith, R., & van Reenen, J. (1999). Market Share, Market Value and Innovation in a Panel of British Manufacturing Firms. *The Review of Economic Studies*, *66*(3), 529–554.

Bound, J., Jaeger, D. A., & Baker, R. M. (1995). Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatory Variable is Weak. *Journal of the American Statistical Association*, *90*(430), 443–450.

Bourreau, M., & Jullien, B. (2018). Mergers, investments and demand expansion. *Economics Letters*, *167*, 136–141.

Bresnahan, T. F. (1989). Chapter 17 Empirical studies of industries with market power. *Handbook of Industrial Organization Volume 2* (pp. 1011–1057). Elsevier.

Bruegel. (2015). Addressing fragmentation in EU mobile telecommarkets. Retrieved March 15, 2019, from https://www.econstor.eu/bitstream/10419/126690/1/833554646.pdf

Bundesnetzagentur. (2018). 5g award - decisions III & IV of 26 november 2018. Retrieved June 6, 2020, from https://www.bundesnetzagentur.de/EN/Areas/Telecommunications/Companies/FrequencyManagement/ElectronicCommunicationsServices/Mobile/BroadbandProject2018/project2018_node.html

Chamberlin, E. H. (1933). *Theory of monopolistic competition*. Oxford University Press, London.

Chang, Y., & Park, C. (2007). Electricity market structure, electricity price, and its volatility. *Economics Letters*, *95*(2), 192–197.

Choi, J. P., & Gerlach, H. (2014). The oxford handbook of international antitrust economics, volume 2: 17. cartels and collusion: Economic theory and experimental economics. *The Quarterly Journal of Economics*, 405–431.

Cohen, W. M., & Levin, R. C. (1989). Chapter 18 empirical studies of innovation and market structure. *Handbook of Industrial Organization Volume 2* (pp. 1059–1107). Elsevier.

COMREG. (2012). Multi-Band Spectrum Award 2012. Retrieved June 6, 2020, from https://www.comreg.ie/industry/radio-spectrum/spectrum-awards/multi-band-spectrum-award-2012/

Der Spiegel. (2018). "Total peinlich": Altmaier schaemt sich fuer deutsches Handynetz. Retrieved March 1, 2019, from http://www.spiegel.de/netzwelt/web/peter-altmaier-schaemt-sich-fuer-deutsches-handynetz-a-1240225.html

Edwards, C. D. (1955). Conglomerate bigness as a source of power. *Business Concentration and Price Policy*, 331–359. Retrieved June 6, 2020, from http://www.nber.org/chapters/c0967

European Commission. (2004). Guidelines on the assessment of horizontal mergers under the Council Regulation on the control of concentrations between undertakings. *Official Journal*, (C031), 0005–0018.

European Commission. (2014). Case M.7018 Telefonica Deutschland / E-Plus - Merger Procedure Regulation.

European Commission. (2016a). Case M.7758 Hutchison 3g Italy / Wind /JV - Merger Procedure Regulation.

European Commission. (2016b). European Commission - PRESS RELEASES - Press release - Mergers: Commission opens in-depth investigation into proposed Hutchison/VimpelCom joint venture in Italy. Retrieved March 1, 2019, from http://europa.eu/rapid/press-release_IP-16-1123_en.htm

European Commission. (2017). Study on spectrum assignment in the european union. Retrieved June 6, 2020, from https://op.europa.eu/en/publication-detail/-/publication/865c787b-aa42-11e7-837e-01aa75ed71a1/language-en

European Commission. (2018). Study on Broadband Coverage in Europe 2017 [https://ec.europa.eu/digital-single-market/en/news/study-broadband-coverage-europe-2017]. Retrieved July 15, 2018, from https://ec.europa.eu/digital-single-market/en/news/study-broadband-coverage-europe-2017

European Commission. (2019). The European Commission's priority on the digital single market [https://ec.europa.eu/commission/priorities/digital-single-market_en]. Retrieved March 15, 2019, from https://ec.europa.eu/commission/priorities/digital-single-market_en

European Communication Office. (2020). Eco frequency information system. Retrieved June 6, 2020, from https://www.efis.dk/

European Parliament. (2019). 5g deployment - state of play in europe, usa and asia. Retrieved June 6, 2020, from https://www.europarl.europa.eu/RegData/etudes/IDAN/2019/631060/IPOL_IDA(2019)631060_EN.pdf

European Union. (2012). Initiation of proceedings (Case M.6570 UPS/TNT Express). *Official Journal of the European Union*, *C186, 55.*

European Union. (2013a). Initiation of proceedings (Case M.6458 Universal Music Group / Emi Music). *Official Journal of the European Union*, *C220, 56.*

European Union. (2013b). Initiation of proceedings (Case M.6663 RYANAIR/AER LINGUS/III). *Official Journal of the European Union, C216, 56*.

European Union. (2016a). Commission Implementing Regulation (EU) 2016/2286 of 15 December 2016 laying down detailed rules on the application of fair use policy and on the methodology for assessing the sustainability of the abolition of retail roaming surcharges and on the application to be submitted by a roaming provider for the purposes of that assessment. *Official Journal of the European Union, L 344*.

European Union. (2016b). Regulation of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). *Official Journal of the European Union, L119*.

Eurostat. (2017). Database, keyword: Isoc_cimobe_use. Retrieved July 15, 2018, from http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=isoc_cimobe_use&lang=en

Evans, W. N., Froeb, L. M., & Werden, G. J. (1993). Endogeneity in the concentration–price relationship: Causes, consequences, and cures. *The Journal of Industrial Economics*, *41*(4), 431–438.

Faccio, M., & Zingales, L. (2019). *Political Determinants of Competition in the Mobile Telecommunication Industry* (Working Paper). Retrieved January 10, 2019, from https://faculty.chicagobooth.edu/-/media/faculty/luigi-zingales/research/faccio_zingales_02-01-2019.pdf

Federico, G., Langus, G., & Valletti, T. (2018). Horizontal mergers and product innovation. *International Journal of Industrial Organization*, *59*, 1–23.

Focarelli, D., & Panetta, F. (2003). Are mergers beneficial to consumers? evidence from the market for bank deposits. *The American Economic Review*, *93*(4), 1152–1172.

Frontier Economics. (2015). *Assessing the case for in-country mobile consolidation - A report prepared for the GSMA* (tech. rep.). Retrieved February 14, 2019, from https://www.gsma.com/publicpolicy/wp-content/uploads/2015/05/Assessing_the_case_for_in-country_mobile_consolidation.pdf

Genakos, C., & Valletti, T. (2011). Testing the Waterbed Effect in Mobile Telephony. *Journal of the European Economic Association*, *9*(6), 1114–1142.

Genakos, C., Valletti, T., & Verboven, F. (2018). Evaluating market consolidation in mobile communications. *Economic Policy*, *33*(93), 45–100.

Giaume, S., & Guillou, S. (2004). Price discrimination and concentration in european airline markets. *Journal of Air Transport Management*, *10*(5), 305–310.

Gilbert, R. (2006). Looking for mr. schumpeter: Where are we in the competition–innovation debate? *Innovation Policy and the Economy*, *6*, 159–215.

Gruber, H. (2005). *The Economics of Mobile Telecommunications*. Cambridge University Press, New York.

Grzybowski, L. (2008). The impact of regulation on the retail prices in fixed-line telephony across the European Union. *Telecommunications Policy*, *32*(2), 131–144.

GSMA. (2012). Information paper - overview of international mobile roaming. Retrieved February 25, 2018, from https://www.gsma.com/publicpolicy/wp-content/uploads/2012/10/GSMA-Information-Paper-on-International-Mobile-Roaming-for-ITU-T-Study-Group-3-FINAL.pdf

GSMA. (2017). Assessing the impact of mobile consolidation on innovation and quality. Retrieved February 25, 2018, from https://www.gsma.com/publicpolicy/wp-content/uploads/2017/07/GSMA_Assessing-the-impact-of-mobile-consolidation-on-innovation-and-quality_36pp_WEB.pdf

Hawthorne, R. (2018). The effects of lower mobile termination rates in South Africa. *Telecommunications Policy*, *42*(5), 374–385.

Houngbonon, G. V., & Jeanjean, F. (2016). What level of competition intensity maximises investment in the wireless industry? *Telecommunications Policy*, *40*(8), 774–790.

HSBC. (2015). Supersonic: European telecoms mergers will boost capex, driving prices lower and speeds higher. Retrieved February 14, 2019, from https://www.orange.com/fr/content/download/33263/1086075/version/2/file/Supersonic+13.04.15.pdf

Jakopin, N. M., & Klein, A. (2012). First-mover and incumbency advantages in mobile telecommunications. *Journal of Business Research*, *65*(3), 362–370.

Jeanjean, F., & Houngbonon, G. V. (2017). Market structure and investment in the mobile industry. *Information Economics and Policy*, *38*, 12–22.

Marshall, G., & Parra, Á. (2019). Innovation and competition: The role of the product market. *International Journal of Industrial Organization*, *65*, 221–247.

Mason, E. (1939). Price and production policies of large-scale enterprise. *The American Economic Review*, *29*.

Motta, M., & Tarantino, E. (2017). The Effect of Horizontal Mergers, When Firms Compete in Prices and Investments. Retrieved March 3, 2019, from https://ideas.repec.org/p/bge/wpaper/987.html

Nickell, S. J. (1996). Competition and corporate performance. *Journal of Political Economy*, *104*(4), 724–746.

OECD. (2014). Wireless Market Structures and Network Sharing. Retrieved February 14, 2019, from https://www.oecd-ilibrary.org/science-and-technology/wireless-market-structures-and-network-sharing_5jxt46dzl9r2-en

Oladunjoye, O. (2008). Market structure and price adjustment in the u.s. wholesale gasoline markets. *Energy Economics*, *30*(3), 937–961.

Parker, P. M., & Roeller, L.-H. (1997). Collusive Conduct in Duopolies: Multimarket Contact and Cross-Ownership in the Mobile Telephone Industry. *The RAND Journal of Economics*, *28*(2), 304–322.

Peitz, M. (2005). Asymmetric access price regulation in telecommunications markets. *European Economic Review*, *49*(2), 341–358.

Peitz, M., & Valletti, T. (2015). Reassessing competition concerns in electronic communications markets. *Telecommunications Policy*, *39*(10).

Prieger, J. E. (2013). The broadband digital divide and the economic benefits of mobile broadband for rural areas. *Telecommunications Policy*, *37*(6), 483–502.

Schmalensee, R. (1989). Chapter 16 Inter-industry studies of structure and performance. *Handbook of Industrial Organization* (pp. 951–1009). Elsevier.

Schmutzler, A. (2013). Competition and investment — a unified approach. *International Journal of Industrial Organization*, *31*(5), 477–487.

Schumpeter, J. A. (1942). *Capitalism, Socialism and Democracy.* Harper & Row, New York.

Shankar, V., Carpenter, G. S., & Krishnamurthi, L. (1998). Late mover advantage: How innovative late entrants outsell pioneers. *Journal of Marketing Research*, *35*(1), 54–70.

Stoughton, N. M., Wong, K. P., & Yi, L. (2017). Investment Efficiency and Product Market Competition. *Journal of Financial and Quantitative Analysis*, *52*(6), 2611–2642.

Sung, N. (2014). Market concentration and competition in oecd mobile telecommunications markets. *Applied Economics*, *46*(25), 3037–3048.

Sutton, J. (1996). Technology and market structure. *European Economic Review*, *40*(3), 511–530.

TeliaSonera. (2006). Yoigo - the smart mobile choice in spain. Retrieved June 6, 2020, from https://www.teliacompany.com/globalassets/telia-company/documents/investors/presentations/2006/teliasonera_presentation_spanish-mobile-opportunity_2006-12-01.pdf

T-Mobile US. (2018). Taking the Next Step in Supercharging the Un-carrier. Retrieved March 21, 2019, from https://www.t-mobile.com/news/taking-the-next-step-in-supercharging-the-un-carrier

Vives, X. (2008). Innovation and Competitive Pressure. *The Journal of Industrial Economics*, *56*(3), 419–469.

Wagner, D. T., Rice, A., & Beresford, A. R. (2013). Device Analyzer: Understanding Smartphone Usage. *Mobile and Ubiquitous Systems: Computing, Networking, and Services*, 195–208.

Wagner, D. T., Rice, A., & Beresford, A. R. (2014). Device Analyzer: Large-scale mobile data collection. *ACM SIGMETRICS Performance Evaluation Review*, *41*(4), 53–56.

Whalley, J., & Curwen, P. (2012). Incumbency and market share within European mobile telecommunication networks. *Telecommunications Policy*, *36*(3), 222–236.

Yun, S. H., Kim, Y., & Kim, M. (2018). Quality-adjusted international price comparisons of mobile telecommunications services. *Telecommunications Policy*, *43*(4), 339–352.

4.7 Appendix

Country	MNO	N
Austria	A1 Telekom Austria	261575
Austria	Deutsche Telekom	3122798
Austria	Orange	81525
Austria	Hutchison 3	268278
Croatia	Deutsche Telekom	2876253
Croatia	Tele2	3485684
Czechrepublic	Telefonica	8467337
Czechrepublic	Deutsche Telekom	4325546
Czechrepublic	Vodafone Group	3818756
France	Bouygues Telecom	5625637
France	Orange	11248623
France	SFR	2710217
France	Free Mobile	4954000
Germany	Deutsche Telekom	17583726
Germany	Kpn	1732691
Germany	Telefonica	7275664
Germany	Vodafone Group	10986000
Hungary	Telenor	2459600
Hungary	Vodafone Group	3393252
Hungary	Deutsche Telekom	973499
Ireland	Vodafone Group	1739755
Ireland	Meteor	420759
Ireland	Telefonica	2318388
Ireland	Hutchison 3	266617
Italy	Vodafone Group	14508268
Italy	Wind	7363394
Italy	Hutchison 3	11744970
Italy	Telecom Italia	18468062
Netherlands	Kpn	30283484
Netherlands	Deutsche Telekom	11379013
Netherlands	Vodafone Group	19396700
Netherlands	Tele2	29417
Norway	Telenor	80862448
Norway	Telia Company	15867937
Norway	Tele2	222590
Romania	Orange	2535989
Romania	Vodafone Group	20988160
Romania	Deutsche Telekom	14787
Slovakia	Orange	2846459
Slovakia	Telefonica	1734217
Slovakia	Deutsche Telekom	1214029
Spain	Telia Company	1720112
Spain	Telefonica	7531097
Spain	Vodafone Group	5036093
Spain	Orange	3221934
Unitedkingdom	EE	49450997
Unitedkingdom	Hutchison 3	18885807
Unitedkingdom	Telefonica	48180537
Unitedkingdom	Vodafone Group	18633643

Table 4.8: *Number of Measurements Considered in the Analysis by Country and Group.*

Statistic	N	Mean	St. Dev.	Min	Max
Share of Areas with G3 or G4 connection	813	0.70	0.14	0.01	1.00
Share of Areas with Mobile Broadbandspeed > 1MBps	813	0.48	0.19	0.001	0.96
Share of Areas with Mobile Broadbandspeed > 2MBps	813	0.42	0.18	0.00	0.88
Share of Areas with Mobile Broadbandspeed > 3MBps	813	0.34	0.17	0.00	0.80
Maximum Speed in MBps	813	44.96	24.07	1.16	72.58
Number of Competitors	813	3.66	0.47	3	4
Herfindahl Hirschman Index - HHI	813	3186.06	459.02	2584	5043
MVNO	813	0.13	0.34	0	1
Position at Market Entry	706	2.23	1.10	1.00	4.00
Mobile Termination Rate in Euro Cents	705	2.25	1.50	0.56	13.88
Mean of Urban Density	813	6.44	3.62	0.64	33.70
GDP per capita in 10000 Euro	813	7.32	3.41	1.30	17.60
Market Size	813	38954764.00	28898079.00	4195240	82122000
Wholesale Roaming Data Cap in Euro Cents	813	21.46	16.59	5	80
Roaming Outgoing Voice Call Cap in Euro Cents	813	25.88	5.92	19	39

Table 4.7: *Urban density and market size are proxy variables which are specified with the mean number of wifi access per mobile cell in each quarter by MNO as well as the population size in each country and quarter respectively.*

	Firm Level		
	No. of Competitors	HHI	
	(1)	(2)	(3)
2nd Entrant	0.003	−1.178	3.969
	(0.017)	(15.436)	(15.556)
3rd Entrant	0.014	−6.672	−7.446
	(0.021)	(15.376)	(15.086)
4th Entrant+	0.001	−0.078	4.251
	(0.018)	(15.465)	(17.009)
Mobile Termination Rates	−0.013**	6.393	15.380***
	(0.007)	(4.730)	(4.495)
Mean Urban Density	−0.002	−2.856	−4.441**
	(0.003)	(1.982)	(2.060)
log(GDP per capita)	−0.226***	117.093	−71.253
	(0.080)	(98.369)	(97.217)
Multimarket Contact	1.602***	−339.394***	
	(0.063)	(45.031)	
Multimarket Contact2	−0.368***	111.520***	
	(0.019)	(13.957)	
Diff Mobile Termination Rates			−31.071***
			(5.690)
Country Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
F-Statistic of Excluded Instruments	336.74***	35.624***	29.824***
Observations	705	705	705
Adjusted R^2	0.873	0.879	0.875

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity and Cluster Robust Standard Errors

Table 4.9: *First-Stage Regression Results at the Firm Level.*

	Market Level	
	No. of Competitors	HHI
	(1)	(2)
Mean Mobile Termination Rates	-0.063	16.087
	(0.060)	(49.978)
Mean Urban Density	-0.386^{***}	286.971^{***}
	(0.081)	(54.969)
log(GDP per capita)	-0.009	-121.297
	(0.390)	(301.437)
Multimarket Contact	0.844^{***}	-97.845
	(0.237)	(148.427)
Multimarket Contact^2	-0.260^{***}	98.995^{***}
	(0.042)	(26.549)
Country Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
F-Statistic of Excluded Instruments	24.958***	10.046***
Observations	128	128
Adjusted R^2	0.891	0.890

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroskedasticity and Cluster Robust Standard Errors

Table 4.10: *First-Stage Regression Results at the Market Level.*

	Firm Level			
	Share of 3G or 4G connection			
	(1)	(2)	(3)	(4)
No. of Competitors	−0.047***	−0.055**		
	(0.016)	(0.027)		
HHI			0.0004***	0.0002**
			(0.0001)	(0.0001)
2nd Entrant	0.030***	0.030***	0.030***	0.029***
	(0.010)	(0.010)	(0.011)	(0.010)
3rd Entrant	0.046***	0.046***	0.048***	0.046***
	(0.012)	(0.012)	(0.014)	(0.012)
4th Entrant+	0.100***	0.100***	0.099***	0.100***
	(0.013)	(0.013)	(0.014)	(0.013)
Mobile Termination Rates	−0.007	−0.007	−0.008*	−0.007
	(0.004)	(0.004)	(0.005)	(0.004)
Mean Urban Density	0.004**	0.004**	0.006***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
log(GDP per capita)	0.209***	0.205***	0.211***	0.223***
	(0.073)	(0.075)	(0.080)	(0.075)
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Instrument Variables	-	mmc	diff mtr	mmc
F-Statistic	34.14***	33.80***	28.55***	32.38***
Observations	705	705	705	705
Adjusted R^2	0.394	0.394	0.270	0.353
Note:				*p<0.1; **p<0.05; ***p<0.01
				Heteroskedasticity and Cluster Robust Standard Errors

Table 4.11: *Regression Results with Different Instrumental Variables at the Firm Level.*

Eidesstattliche Erklärung

Ich 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. Die Arbeit wurde bisher in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht.

Düsseldorf, 1. September 2020 ____________________

Nicolas Wellmann