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Master Thesis

Beyond digital disruption: Estimating the socio-economic impacts of the sharing economy

Evidence from China

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Abstract

Internet-facilitated sharing platforms, such as Airbnb or Uber, have experienced meteoric growth in recent years, despite essential controversy whether externalities of the digital evolution are beneficial or detrimental for its various stakeholders. This thesis contributes to the debate with systematic evidence, demonstrating nontrivial socio-economic impacts in the world's largest market: China. Effects of the staggered market adoption of China's leading e-hailing platform Didi Chuxing are explored, utilizing longitudinal administrative, social-survey and search-engine data in a variety of empirical strategies. Results indicate a 4,5% decline of mobility prices, a 19% increase of self-employment in the mobility sector and an intersectoral mitigation of income inequality throughout the period of observation. Hence, this work augments academic research and can provide policy-makers with valuable insights, when designing appropriate regulatory frameworks.

摘要：

近年来如优步和爱彼迎这类以互联网和科技进步为基础的共享平台在具体的利弊权衡上饱受争议，却始终无法阻挡它们迅速发展的步伐。因此，本篇论文重点讨论了嘀嘀打车——中国最大的网约车服务平台，对中国社会经济产生的巨大影响。本文结合了政府年份统计数据，社会调查和搜索引擎提供的大数据对此问题进行了系统综合的探讨。调查年限范围内的结果表明网约车服务平台降低了出行成本 4.5%，增加了运输业自主雇佣 19%，且有效地改善了跨行业收入不均的问题。本篇论文的结论可以有效地制定行业规范时为决策者提供宝贵的见解。

(Translated by Qiong Wu)

Kurzfassung

Trotz kontrovers diskutierter Externalitäten erzielen internetbasierte Sharing-Economy-Plattformen, wie etwa Uber oder Airbnb, rasante Wachstumsraten. Um zu einem fundierteren Verständnis dieser digitalen Innovationen beizutragen, analysiert die vorliegende Arbeit den weltgrößten Markt: China. Mittels verschiedener ökonometrischer Modelle werden administrative Daten, sozialwissenschaftliche Panels und Suchmaschinen-Volumina ausgewertet, um sozio-ökonomische Effekte der größten Chinesischen Ride-Hailing-Plattform Didi Chuxing zu quantifizieren. Die Ergebnisse weisen auf eine Abnahme von Mobilitätspreisen um 4,5%, eine Zunahme selbständiger Beschäftigung im Mobilitätssektor um 19% sowie eine übergreifende Abschwächung von Einkommensungleichheiten im Beobachtungszeitraum hin. Somit ergänzt die Arbeit die wissenschaftliche Forschung und unterstützt eine evidenzbasierte Gestaltung durch politische Entscheider.

Preface

In anticipation of this academic thesis, I would like to express my appreciation to Prof. Dr. Jarko Fidrmuc (Zeppelin University) for the advice, supervision and funding by the faculty and Prof. Dr. Marcel Tyrell (Witten/Herdecke University) for the supervision of the submitted paper. I would also like to thank Prof. Dr. Jeffrey Towson (Peking University) for establishing contact with Didi Chuxing. Furthermore, I am gratefully indebted to Ms. Qiong Wu (Freie Universität Berlin) and Ms. Xin Yue (Peking University) for helpful comments and support in the retrieval of Baidu Index data. Last but not least, I would also like to acknowledge with much appreciation my family and girlfriend for all their efforts in providing helpful discussions, comments and advice during the preparation of this thesis.

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List of Abbreviations

ATM	Automatic teller machine
CFPS	China Family Panel Studies, Peking University
C.p.	Ceteris paribus (everything else equal)
CPI	Consumer price index
DID	Difference-in-Difference
GPS	Global positioning system
IPO	Initial public offering
NBS	National Bureau of Statistics, China
NSE	Number of self-employed individuals
O.a.	On average
O.a.c.p.	On average ceteris paribus
OVB	Omitted variable bias
P.a.	per annum (year)
P.d.	per diem (day)
P.p.	Percentage points
RMB	Chinese Renminbi (Yuan)
SE	Sharing economy
SD	Standard deviation
SOE	State-owned enterprises
TB	Terabyte
TSP	Transport, storage and post
USD	US-Dollar
YOY	Year-over-year

Glossary

μ	Arithmetic mean
σ	Standard deviation
≈	Approximately equal
Y	Dependent variable
α	Intercept
i	Entity (e.g. province)
t	Period (e.g. year)
β	Coefficient of independent variables
$Baiduint_{i,t}$	Baidu Index and market entry interaction term
ϑ_s	Coefficient of control variable s
$\mathbf{X}_{\boldsymbol{i,t}}$	Set of control variables
θ_i	Individual fixed-effects
γ_t	Time fixed-effects
$\varepsilon_{i,t}$	Idiosyncratic error term
$z_{i,t}$	Omitted variable
$\boldsymbol{Z}_{i,t}$	Set of omitted variables
c	Constant

1 Introduction[1]

Each generation of technological innovation has caused a substantial change in the way how individuals interact within the economy (Card & DiNardo, 2002; Z. Li, Yili, & Zhang, 2018). Since the industrial revolution has reshaped society beyond recognition, this mutual impacts between technology and society have been a well-discussed issue for economists (Blinder, 2006; Çalışkan, 2015; J. Greenwood, 1999; Rubinstein, 1977). During the last decades, the advent of the internet has fundamentally altered the organization of economic activities. Drawing on information technology, platform businesses and digital marketplaces enable transactions among decentralized and location-independent supply- and demand-side participants through innovative forms of value creation (Täuscher & Laudien, 2018; Vallas, 2018). Some two-sided platforms of the early 21st century (e.g. Amazon and Facebook) are nowadays among the world's most valuable corporations and new business models are constantly emerging: platform businesses account for 14% of a total of 326 start-ups worldwide with a company valuation of over 1 billion US-dollars (Fortune, 2019; Parker, Van Alstyne, & Jiang, 2016; CBInsighty, 2019). Especially since the global economic recession in 2008, a sub-sector of platform businesses has attracted much attention due to the success of prominent companies such as Airbnb and Uber (Bergh, Funcke, & Wernberg, 2018). The so-called "Sharing Economy" (hereafter referred to as "SE") utilizes the basic principles of decentralized networks by facilitating the sharing or renting of space, assets and labour in real time (Ferreri & Sanyal, 2018; Ganapati & Reddick, 2018). In a variety of sectors, providers share similar qualities as e-commerce or social media platforms but exploit the technology in a distinctive way: while the former focus on commercial goods transactions or peer-to-peer communication, the latter enable people to temporarily share their underutilized assets (Ganapati & Reddick, 2018). The diversity of sectors covered by SE-platforms has increased rapidly, as it turns out that various commodities can be shared, from clothes (e.g. Yerdle), meals (e.g. EatWith) to energy (e.g. Yeloha) (Magno & Bentoglio, 2016). The public perception, however, is largely

[1] The numeric and decimal notation in this thesis corresponds to the German specification.

concentrated on the most popular platforms, especially the ride-hailing services Uber (USA), Didi Chuxing (China, hereafter "Didi"), and the accommodation supplier Airbnb (USA) (Geissinger, Laurell, & Sandström, 2018). Although the concept of sharing itself is no novelty, certain common factors of digital SE-marketplaces substantiate a competitive advantage in incumbent markets: a large "mobile-first" product design that allows users to demand services from anywhere at any time has proven to be an effective strategic response to intense price-competitive markets with scarce innovations (Ganapati & Reddick, 2018; Kenney & Zysman, 2016). SE-companies were credited to effectively reduce transactions costs between peers based on sophisticated matching algorithms and the externalisation of the information supply to the users (X. Wu & Zhi, 2016). In addition, peer evaluations and rating systems have solved the critical trust problem among third parties and prevent for moral hazard (Avital, Hjalmarsson, & Carroll, 2015; Mittendorf, 2017; S. B. Yang, Lee, Lee, & Koo, 2018). A study by *Mazzella, Sundararajan, Butt d'Espous, and Möhlmann (2016)* surveying users of the carpooling app blablacar indicates that 88% of the respondents set higher trust in a blablacar-driver they never met before than in their neighbours, co-workers or social media contacts. Empowering trust and autonomy amongst users enables SE-services to eliminate costly (offline) intermediaries and facilitate direct supplier-to-consumer exchange (Avital et al., 2015; Schor & Attwood-Charles, 2017). Moreover, a changing nature of consumer behaviour is gradually served by the SE: to re-use existing goods attracts a growing number of consumers who care about environmental benefits as well as providers that share excess capacity with the public (Ganapati & Reddick, 2018; Magno & Bentoglio, 2016; Schor, 2017). Some researchers argue that this trend, collectively known as "collaborative consumption", is part of a wider set of seismic shifts in the way how economic activities are organized. A shift with dramatic impacts on the supply and consumption of goods (B. Cohen & Kietzmann, 2014; Ferreri & Sanyal, 2018). In summary, these qualities – which are examined in more detail in section 2 – have led to a remarkable proliferation of the SE in the last decade. The large number of users and suppliers additionally suggest, that platform-mediated sharing is not just a temporary appearance but may become an inseparable part of the economy (Schor, 2017; Yaraghi & Ravi, 2017). As digital platforms, SE-companies exploit network effects (Guo, Xin, Barnes, & Li, 2018; Parente, Geleilate, & Rong, 2018), which potentially foster a “winner-takes-it-all” scenario and accelerate exponential growth (Belleflame & Peitz, 2016). Thus, the market valuation of some of the most successful sharing platforms has surpassed long-established competitors: in May 2018, Airbnb offered more than 5 million temporary renting spaces in 81.000 cities across the globe. Its valuation of USD 31 billion made the company more valuable than the world’s largest hotel chain Intercontinental Hotel Group[2,3] (Forbes 2018, recode, 2019). Taken together, Uber and its Chinese competitor Didi served more than 11,4 billion trips in 2017 (Uber, 2017; ChinaDaily, 2018a). At its initial public offering (IPO) in May 2019, Uber was valued at USD 69 billion, while Didi reached a valuation of USD 56 billion in the company’s most recent funding in July 2018 (Reuters, 2018; cnvc, 2018). At the respective time of investment, Uber reached a higher market value than the world’s largest car manufacturer Volkswagen, while Didi surpassed China’s largest vehicle producer Shanghai Automotive Group[4,5]. On an overall level, the SE is expected to experience rapid growth from sales revenues of USD 15 billion in 2014 to approximated USD 335 billion in 2025 with tremendous effects on consumers, workers and industries (Osztocits, Koszegi, Nagy, & Damjanovics, 2015).

Operating at this scale, sharing platforms deploy a huge number of contingent workers that provide goods or services beyond intrinsic motivations. Recent studies examining the intention to participate in the SE indicate that significant shares of peers are driven by economic motivations (Böcker & Meelen, 2017; Ferreri & Sanyal, 2018; Magno & Bentoglio, 2016; Möhlmann, 2015). McKinsey-analysts *Manyika et al. (2016)* estimate the size of the independent labour force in the US and EU-15 at about 162 million people – or 20-30% of the total economically-

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[2] Hotel chain size was ranked according to the number of rooms.

[3] The market capitalization of IHG (FRA: IC1B) in May 2018 was captured from Yahoo Finance.

[4] Motor vehicle manufacturers are ranked according to global sales volume.

[5] The market capitalization of Volkswagen and Toyota corresponds to the month of the respective investment in Uber and Didi Chuxing. The market value was investigated as follows: Number of outstanding shares (month) ∗ Average share price (month). Numbers of outstanding shares were sourced from *Volkswagen (2019)* and *SAIC Motor (2019)*. The average share prices (VOW.DE and 600104:CH) were calculated with data from Yahoo Finance.

active population. In light of this multinational increment, manifolds of researchers controversially discuss the impacts of the trend towards a more flexible and on-demand form of labour and consumption (Avital et al., 2015; Chee, 2018; De Stefano, 2015; Schor, 2017; S. B. Yang et al., 2018). On the one hand, SE-companies claim to constitute several socio-economic benefits by providing flexible incomes for low educated or impecunious people, versatile offers that are affordable for large parts of society, reduced ecological footprints and empowered social connection, which has triggered a set of empirical research (Berger, Chen, & Frey, 2018; Böcker & Meelen, 2017; Cramer & Krueger, 2016; X. Wu & Zhi, 2016; Zervas, Proserpio, & Byers, 2013). On the other hand, critical commentators emphasize the unintended economic and social externalities: rising labour market insecurity with flexible workers who depend on piecemeal jobs without workplace- or social security benefits, a weakened union structure, a "raise-to-the-bottom" for wages and prices in ultra-liberal markets and an aggravation of inequality as property owners are disproportionally privileged (Cherry & Pidgeon, 2018; Ferreri & Sanyal, 2018; Ganapati & Reddick, 2018; Jing & Sun, 2018; Schor, 2017; Vallas, 2018). This growing size of the SE causes a challenging situation for politicians (Ferreri & Sanyal, 2018; Hira & Reilly, 2017). Despite increasing intention on the political agenda, policy-makers are confronted with ambiguous and divergent indications of the impact on society. Especially, when evolving an appropriate regulatory framework, which should promote innovative aspects but effectively limit negative externalities (Ganapati & Reddick, 2018). Until the rise of the SE, independent work has rarely been the focus of politics, in part because its many occurrences impede quantifications of economic and social influences (Burtch, Carnahan, & Greenwood, 2016). However, the rapid growth of SE-business models, operating with flexible labour, potentially expose effects on important policy indicators. The proliferation allows obtaining a profound understanding of an increasingly relevant form of labour organization and its impacts on society. Its expansion inevitably entails an urgent need for evidence to facilitate informed policy decisions. Hence, this thesis aims to contribute with a systematic empirical evaluation in order to extend the state of knowledge on the impacts of the SE on labour and society.

Despite its increasing relevance, quantifying the effects of sharing platforms on incumbent markets is complex. On the one side, due to their large variation among multiple industries and across country borders; on the other side, due to the scarcity of available data (Conway, Salon, & King, 2018; De Stefano, 2015). Therefore, the most common research approach is to examine a fragmented market, while several studies create a holistic picture of the overall phenomenon (e.g. Cramer & Krueger, 2016; Möhlmann, 2015; Yang et al., 2018). Online ride-hailing (hereafter “ride-hailing” or “e-hailing”), which provides app-based on-demand car, taxi, limousine and bus transport by semi-professional drivers, is particularly suitable for several reasons: First, e-hailing is one of the earliest and best-settled subsectors in the SE and expected to grow to a revenue size of USD 285 billion in 2030 (Burgstaller, Flowers, Tamberrino, Terry, & Yang, 2017). The sector’s largest companies Uber and Didi combined have raised more than USD 45 billion in venture capital[6] serving 625 Million customers or 8,3% of the world’s population with 34 Million drivers[7] accounting for 0,67% of the world’s total working age population (Crunchbase, 2019; Index, 2019; Uber, 2019; Didi Chuxing, 2019a; Worldbank, 2019a&b). Moreover, *Geissinger et al. (2018)* and *Sutherland & Jarrahi (2018)* identified that approximately 40% of the total news content and 25% of the research publications on the SE are related to individual mobility. This demonstrates the prevailing public and academic interest in the subject. Second, recent studies indicate that providers and users consider ride-hailing especially for individual motives (e.g. a flexible income, convenience and cost efficiency), while altruistic motivations are more prevalent in other sectors of the SE, such as meal sharing (Böcker & Meelen, 2017; Geissinger, Laurell, Öberg, & Sandström, 2019; Zhu, So, & Hudson, 2017). This professional approach has substantially fostered the sectors’ growth, increasing the likelihood that socio-economic effects occur and can be observed. Third, despite location-independent subsectors of the SE, the impacts of ride-hailing can be observed and quantified at a local level. The business model seems to affect several indicators, which prove to have a

[6] As of 03.2019: Uber (USD 25,5 billion), Didi Chuxing (USD 20,6 billion).

[7] Self-reported figures by the companies. As of 03.2019: Uber (75 million customers, 3 million drivers), Didi Chuxing (550 million customers, 31 million drivers).

high relevance from an economic as well as political perspective: customer demands can only be served by a local labour supply with potential impacts on the regional and sectoral employment, unemployment rate and labour force participation. In this context, flexible, direct and intersectoral wage effects may occur, as market barriers are low and almost independent of inhibiting individual characteristics (e.g. age or education). Thereby, SE-services may empower individuals to earn a primary income or to receive a supplement to compensate for fluctuations. Eventually, the mobilization of underutilized capacity and the extension of transportation supply may substantiate declining costs for individual mobility which is detectable in the accordant consumer price index (CPI) (Berger, Chen, et al., 2018; J. Hall & Krueger, 2018; Vallas, 2018). These indicators are of paramount importance to substantiate evidence-based policy decision: Active politics in employment and income distribution are fundamental principles of the welfare state (McCall & Percheski, 2010; Vooren, Haelermans, Groot, & Maassen van den Brink, 2019). Additionally, consumer price levels – influenced by tax or subsidy regulation – turned out to be a sensitive topic. The recent "yellow-vests" demonstration in France, originally triggered by an announcement to increase fuel tax levels, exemplifies the relevance for politicians to govern the price structures of mobility (CNN, 2018).

It is noteworthy that empirical research on the interactions of e-hailing and incumbent markets is almost exclusively conducted with data of the US-based company Uber (Berger, Chen, et al., 2018; Cramer & Krueger, 2016; Geissinger et al., 2018; Lee, Chan, Balaji, & Chong, 2018; Z. Li et al., 2018). This is surprising since Uber operates in a highly competitive market. Applying a company exclusive study, thus, only reveals insights about a fragment of the industry and at most about the countries where Uber is available. As argued above, the prevalence of this empirical approach is caused by a necessary constraint due to distinguishable corporate characteristics. However, a holistic picture can only be provided if different corporations are subject to examinations. The relevance of this argument becomes more obvious, when a global perspective is considered: market-size estimations of 2017 suggest that the Chinese market itself surpasses the combined international market in terms of total trip numbers and revenues – but Uber sold its Chinese business in 2016 (Stone & Chen, 2016; Tsang, Boutot,

& Cai, 2018). In addition, a global study by *Nielsen (2014)* with 30.000 participants suggests, that the willingness to share their property exceeds the global average of 67% by 12,5 p.p. among citizens in Asian countries, with China showing the top score of 94% across all countries. This indicates that the long-term growth potential of the SE is disproportionally larger in China and Asia than in other economies. In case a study relies on the development of a single company, China is also more representative as about 95% of the Chinese e-hailing market is served by the monopolist Didi Chuxing. All these arguments combined indicate that the Chinese market is indispensable to convey a holistic picture – and has been neglected by the English literature. This thesis aims to address this gap of evidence by empirically exploring the impacts of sharing platforms on employment, wages and prices in China between 2008 and 2018. To the best knowledge of the author, this is the first approach documented in English language that seeks to assess the research question in the described context (June 2019). To examine the subject, both aggregated provincial data from the National Bureau of Statistics (China) between 2008 and 2018 as well as nationally-representative microdata from the China Family Panel Studies (CFPS) in the periods 2010 and 2016 are evaluated. Moreover, the market penetration of Didi, as leading Chinese e-haling provider, is approximated utilizing search engine volume data quantified by Baidu-index.

The remainder of this thesis is organized as follows: section 2 provides an overview of advances of the SE-market in China and illustrates qualities of key stakeholders such as users and drivers. The subsequent section 3 presents relevant literature related to the sector and elucidate the formation of research hypotheses. Details about the data setup and the econometric strategy are provided in section 4, which is followed by the presentation of the estimation results and a series of robustness checks to strengthen the evidence validity in section 5. Section 6 eventually embeds the obtained results in economic theory and related literature, discusses the socio-economic implications and conveys concluding remarks on the study.

2 The past, current and future ride-hailing market in China

2.1 The advent of ride-hailing in China

While the expansion of the US-based companies Uber and Lyft triggered a great body of articles and scientific papers in the English-speaking public media and research, the Chinese market remains widely unobserved. Therefore, this section will review past, current, and expected market developments and examine key stakeholders within the Chinese e-hailing sector.

In the near future, the Chinese ride-hailing market is likely to grow due to changes in economy, urban density, mobility infrastructure and travel preferences. Table 1 displays the provincial growth rates of 31 Chinese provinces[8] with regard to population, urbanisation, gross regional product (GRP) per capita, number of taxis, transit passenger kilometres and private car possession in the period of 2008-2017. Fixed-effects regression results including all data between 2008 and 2017 reveal positive and significant impacts ($p<0,1$) of the amount of population, number of taxis and GRP per capita on private car possession, while transit passenger kilometres are significantly negative, and urbanization shows no significant effect, c.p. (Appendix I.). This suggests that public transit is an effective substitute for cars in daily mobility, while taxis are a complementary service. However, while transit passenger kilometres increased by 20% o.a. across the provinces, private car possession accounts for an average 605% increase in the equivalent period. Considering a population growth of 7% o.a. this development highlights a disproportional pressure on the mobility infrastructure. Yet beneath this evolution, cities with a high population density – suggested by the 22% increase o.a. of urbanization ratio – face difficulties in providing sufficient mobility capabilities[9]. Between 2008 and 2017, Beijing shows a perceptible development in population and private vehicles with a 23% and 93% increase, respectively.

[8] The focus of this thesis is on the development of Mainland China. Due to certain peculiarities (e.g. different currencies and regulation) special administrative regions and autonomous areas, such as Hong-Kong, Macao and Taiwan, are excluded from any statistics and discussions in the remainder of this paper.

[9] Three of the five provinces with a declining urbanization ratio (Anhui, Jiangsu and Hebei) boarder to the 1th Tier cities Beijing and Shanghai, which suggest that inhabitants consider moving between the provinces rather than to the local cities.

But the amount of taxis remains almost constant with a 3% rise and transit passenger kilometres even show a decline of -24%. Shanghai's population grew by 13% c.p., while the number of taxis declines by -3%. The city was capable to exp-

Provincial growth rates of socio-economic indicators and mobility capacity
China, (2008 vs. 2017)

Province	Resident Population	Urbanization Rato	GRP per Capita	Number of Taxis	Transit Passenger Km	Private Car Possession
Beijing	23%	2%	3%	106%	-24%	93%
Tianjin	32%	7%	0%	109%	14%	216%
Hebei	8%	-36%	13%	97%	29%	514%
Shanxi	9%	27%	7%	96%	-1%	415%
Inner Mongolia	3%	20%	7%	83%	9%	525%
Liaoning	1%	12%	2%	69%	18%	490%
Jilin	-1%	6%	2%	134%	5%	493%
Heilongjiang	-1%	56%	13%	93%	2%	454%
Shanghai	13%	0%	-3%	93%	52%	280%
Jiangsu	3%	-21%	20%	168%	19%	514%
Zhejiang	9%	50%	16%	122%	-2%	428%
Anhui	2%	-37%	12%	199%	-3%	907%
Fujian	7%	0%	35%	177%	35%	518%
Jiangxi	5%	109%	36%	173%	26%	1121%
Shandong	6%	27%	10%	121%	-13%	516%
Henan	1%	39%	1%	144%	18%	702%
Hubei	3%	91%	33%	203%	41%	780%
Hunan	8%	30%	13%	173%	23%	755%
Guangdong	13%	10%	20%	116%	18%	333%
Guangxi	1%	29%	25%	160%	6%	764%
Hainan	8%	-33%	82%	174%	3%	629%
Chongqing	8%	28%	76%	210%	29%	851%
Sichuan	2%	-41%	16%	188%	-11%	547%
Guizhou	0%	58%	151%	282%	83%	863%
Yunnan	6%	42%	20%	172%	31%	538%
Tibet	15%	41%	65%	188%	47%	349%
Shaanxi	3%	35%	27%	190%	17%	632%
Gansu	3%	38%	15%	129%	32%	1174%
Qinghai	8%	30%	31%	139%	80%	842%
Ningxia	10%	29%	3%	159%	15%	853%
Xinjiang	15%	25%	36%	127%	6%	659%
Average:	**7%**	**22%**	**25%**	**148%**	**20%**	**605%**
Classification:	**< 0%**	**0-1%**	**1-30%**	**30-100%**	**100-200%**	**>200%**

Table 1: Provincial growth rates of socio-economic indicators and mobility capacity (own illustration, data from NBS, 2019)

pand the transit passenger kilometres by 52% but an increase of 280% in private car possession significantly surpasses this advance. Car ownership has originally been an important status symbol in China; a purchase that many Chinese people were able to afford with constantly rising GRP and disposable income (NBS, 2019). Nevertheless, the intense growth of private cars may decline, as consequences of asphyxiating pollution and overwhelming traffic congestion in major cities impair the attractiveness of individual car ownership: (1) introduced in 1994, Shanghai became the first Chinese city with a vehicle restriction policy. Under the scheme of a plate ceiling auction, Shanghai restricted the purchase of new automobiles by distributing limited license plates. In February 2018 the average winning price was about USD 13.800 – above the typical price for a domestic car (Global Times, 2018). Consequently, residents showed a negative attitude towards the fairness of the system, as wealthy inhabitants benefit disproportionally (X. Chen & Zhao, 2013). Beijing adjusted the mechanism in 2011 with the introduction of a lottery system that randomly allocates vehicle licenses – causing long waiting times but limited additional costs. However, the odds to win a license at the bimonthly draw are infinitesimal: in April 2018, 2,8 million participants contended for only 6.460 plates – resulting in a probability of 0,2% – thereby, naturally curtailing the number of new vehicle registrations (J. Yang, Liu, Qin, & Liu, 2014; The Economist, 2018). In 2014, Guangzhou and Guiyang adopted the system. Considering the negative externalities of private car use, the government potentially further limits the availability of new licenses (J. Yang et al., 2014). (2) Bain & Company researchers *Tsang et al. (2018)* interviewed 2.000 Chinese consumers in 2014 and 2017. The findings indicate a changing consumer behaviour, suggesting that car ownership as a status symbol is fading. While in the 2014 survey 60% of the respondents associated car ownership with a higher social status, the proportion decreased to 40% in 2017. Confronted with a direct question in the 2017 survey on the relevance of cars as status symbol, 50% of the participants stated that the importance has decreased (Tsang et al., 2018). Overall commuting time and punctuality are the primary concerns of consumers in the current mobility. 25% of each, car owners and potential buyers, cited traffic congestion as primary factor to give up or refrain from purchasing a car. For 23% of each group, the availability of convenient mobility alternatives is the second most frequent reply (Tsang et al., 2018). These developments are likely to slow down the growth of car ownership in China – and indeed – for the first time in almost three decades, vehicle wholesales fell by 17,7% (YOY) in January 2019 (Bloomberg, 2019; Financial Times, 2019). But the rising economic status ultimately changed individual mobility demands, exemplified by 60% of respondents who increased their mobility frequency in the last two years (Tsang et al., 2018). Waning attractiveness of car ownership and high demands on individual mobility fuel the business model of ride-hailing, as it encounters the trends: recent studies exemplify that private vehicles go unused for 95% of their lifetime while depreciation accounts for the most relevant share of costs (Burgstaller et al., 2017). In contrast to the low occupancy levels of private cars, e-hailing services can quickly redeem the rising cost of ownership from vehicle restriction policies. Mobilizing underutilized car capacity leads to fewer required vehicles and facilitates a more effective resource allocation. Ride-hailing thereby reduces the total number of cars while providing an affordable and individual form of mobility. This customer value proposition boosted the number of yearly ride-sharing trips from 0 in 2012 to approximately 7,4 billion in 2017 (Roland Berger, 2017), and is likely to grow further as displayed in illustration 1. The relative share of ride-hailing services in daily mobility is expected to rise from 11% to 32% between 2015 and 2050, with a population induced overall mobility expansion of 49%. If macroeconomic and mobility trends remain as forecasted, e-hailing businesses will additionally benefit from the domestic consumption upgrade and capital inflow (A. Zhou, Liu, Zhou, Peng, & Wang, 2019). The sector's increasing relevance and the maturity of services substantiate constant growth as highlighted in illustration 2. Industry experts estimate overall turnovers to rise by a factor of 2,94 to a total of USD 62,1 billion, with a slightly lower but still substantial customer development by a factor of 1,7 to 380,8 million users in 2023. Considering the global market, Chinese ride-hailing companies achieved USD 20 billion gross-revenues in 2016 – more than 50% of the world's total value (Tsang et al., 2018). China is likely to maintain its leading position in the sector: analysts assess the global market growth at USD 133,4 billion in 2023, with China accounting for 46,5% of total revenues (Statista, 2019a).

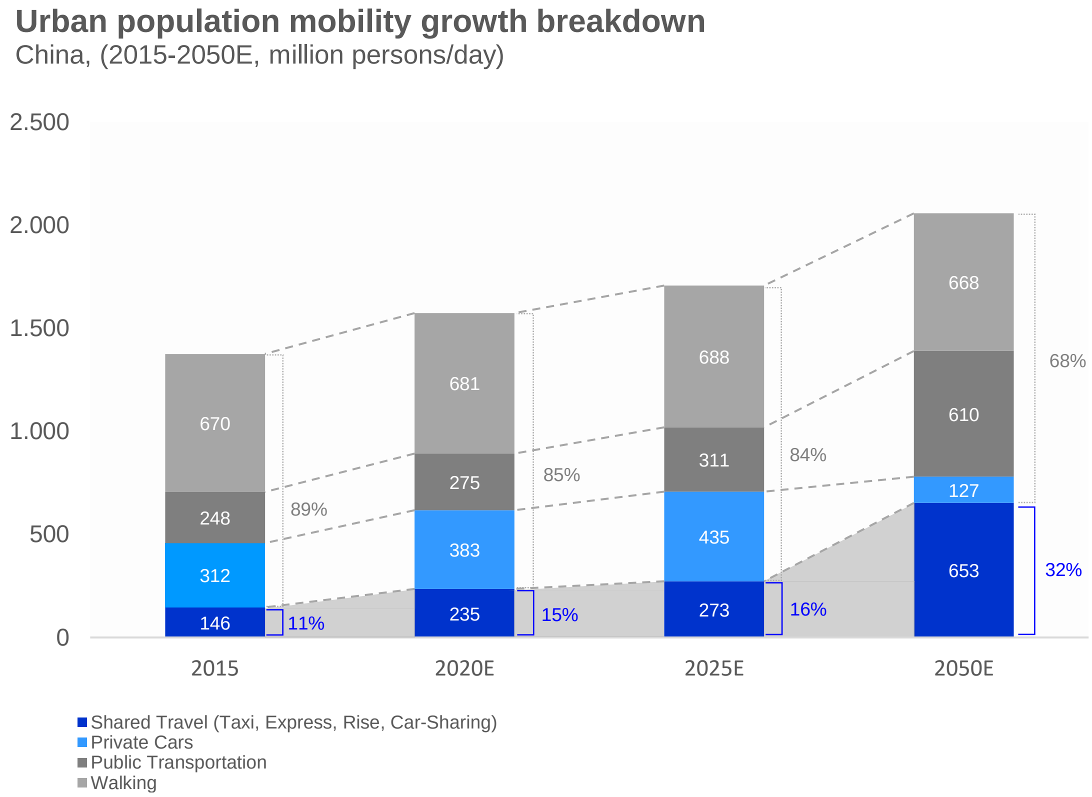

Illustration 1: Urban population mobility growth breakdown (2015-2050E) (modified, data from Zhou et al., 2019)

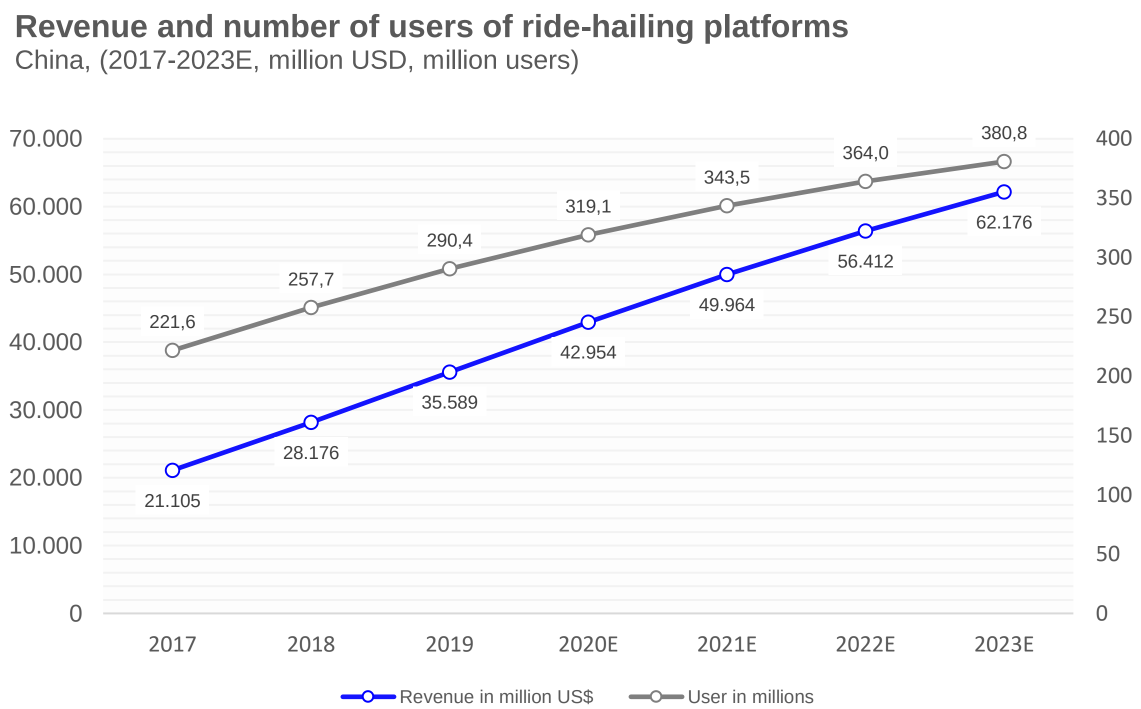

Illustration 2: Revenue (left axis) and number of users (right axis) of ride-hailing platforms (2017-2023E) (own illustration, data from Statista, 2019a).

2.2 Market distribution

Despite its size, the Chinese ride-hailing sector is highly consolidated with a monopoly position of Didi Chuxing: in Q2/2018, the market of approximately 19,3 million daily orders was divided in 5% premium car orders and 95% standard express services. Didi supplies 99% of the express-market and 74% of the premium rides, overall serving 96,6% of the total orders (see illustration 3). A very similar picture appears if revenues are compared as presented in illustration 5.

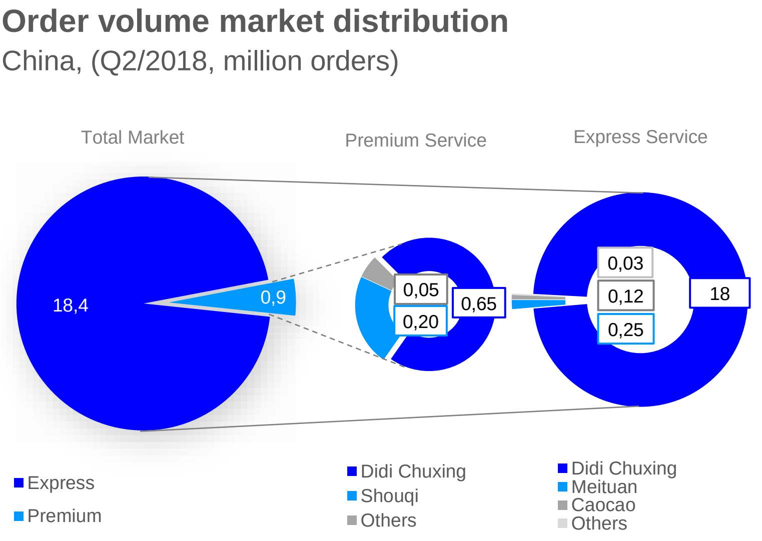

Illustration 3: Order volume market distribution (Q2/2018) (own illustration, data from Zhou et al., 2019).

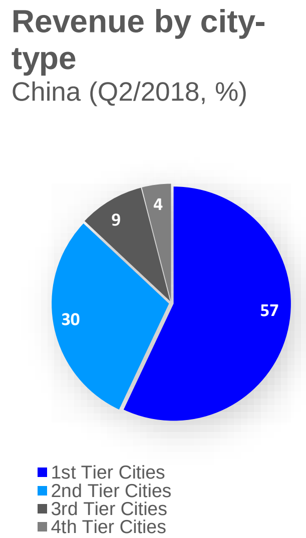

Illustration 4: Revenue by city-type (own illustration)

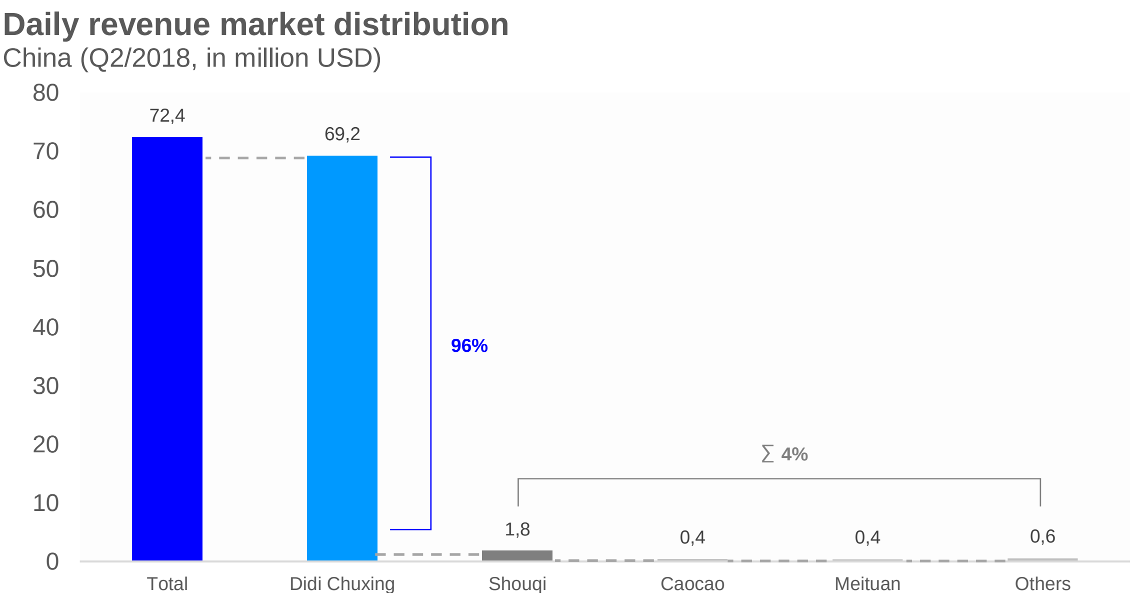

Illustration 5: Daily revenue market distribution (Q2/2018) (modified from Zhou et al., 2019).

Again, Didi Chuxing generates 96% or USD 69 million of the daily total market revenue while competitors contend about 4% or an equivalent of USD 3,2 million (A. Zhou et al., 2019). The revenue distribution across cities shows a strong focus on high-density urban areas, as visualized by illustration 4. 1st Tier and 2nd Tier cities[10] combined account for 86% of the total turnover, while the remaining 350 to 450 cities only add a share of 13%. A more detailed examination of the regional development of Didi Chuxing is provided in subsection 2.3 and 4.6.

2.3 Didi Chuxing

Founded in September 2012 as Didi Dache,[11] the company adapted the business model invented by ride-hailing first movers Uber (USA) and Hailo (UK) to the Chinese market (Stone & Chen, 2016). The original design primarily focused on the incumbent taxi industry, allowing users to hail a taxi via an app. At the beginning of 2014, Didi and competitors established today's main business with a turn towards private car owners, whose number quickly exceeded the taxi drivers (J. Y. Chen, 2018). In several funding rounds, Didi raised a total of USD 20,6 billion of venture capital (03/2019) from prominent companies, including Chinese tech giants Baidu, Alibaba and Tencent as well as international investors such as Apple, and Softbank (Index, 2019). Between 2012 and 2015, Didi rapidly diffused across the Chinese provinces as shown in illustration 6. The expanding business was additionally flourished by two major acquisitions, substantiating today's dominant market position. The merger with Kuaidi Dache in 2015 created a powerful Chinese counterpole to foreign competition by Uber, which launched its app in late 2014 (Reuters, 2015; The Wall Street Journal, 2014). Powerful enough to outmaneuvere Uber from the Chinese market in a USD 35 billion acquisition in August 2016, trading Uber's 22,2 million active users against a 17,7% equity

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[10] 1st Tier: Cities with more than 200.000 daily orders (e.g. Beijing, a total of 6).
2nd Tier: Cities with daily order ranking 7-47 (e.g. Chongqing, a total of 40).
3rd Tier: Cities with daily order ranking 47-100 (e.g. Lijiang, a total of 54).
4th Tier: Remaining cities with order ranking >100 (e.g. Suining, a total of >300).
The classification is based on the internal system of Didi Chuxing (A. Zhou et al., 2019).

[11] „Dache" means „to call a taxi" in Mandarin Chinese (J. Y. Chen, 2018).

Spatial diffusion of Didi Chuxing in China

Hongkong, Macao and Taiwan excluded, (2012-2015)

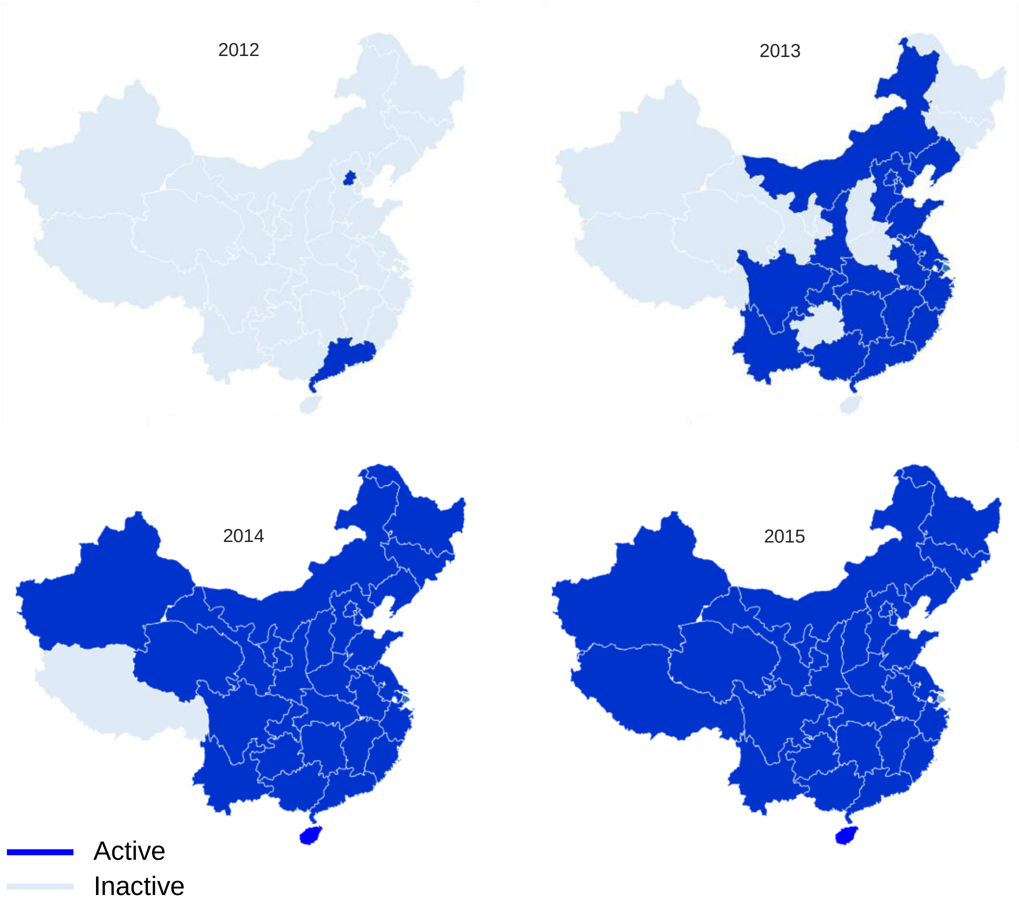

Illustration 6: Spatial diffusion of Didi Chuxing in China (own illustration)

share of Didi and USD 1 billion in cash (Stone & Chen, 2016). Today, Didi reports serving 550 million customers with a daily demand of more than 30 million rides, served by 31 million drivers (Didi Chuxing, 2019a). Customers have to fulfil a simple in-app registration process and select a payment method (e.g. WeChat pay) to connect to Didi's service. Potential Didi-drivers have to pass a more sophisticated verification, although the requirements are still straightforward compared to the taxi business, which is among the strictest regulated sectors in China (Y. Li & Chen, 2016; X. Wu & Zhi, 2016). In terms of regulation, ride-hailing and taxi drivers are treated as mutually exclusive groups with a strong dichotomy of exigencies. Taxi companies must meet criteria in terms of insurance and car condition while drivers must take several examinations to receive a license by the transportation agencies at the county level. Once a license has been obtained, monthly fee payments occur with the total number of taxicabs and prices charged to customers being controlled by the local government authorities (J. Y. Chen, 2018; B. W. Huang, Yin, & Zhou, 2017; Y. Li & Chen, 2016). With a restricted fleet capacity and fixed price levels, the flexibility of taxi companies is considerably limited while monthly fee-payments put additional pressure on the business. E-haling services operate without limitation in fleet-size and price levels, entry barriers are according to self-controlled standards[12] and drivers pay a case-to-case commission for each ride with no monthly fixed fees (J. Y. Chen, 2018). Thus, Didi potentially attracts the 170 million Chinese car owners and the additional 150 million driving license holders without a vehicle (NBS, 2019; Roland Berger, 2017). The platform, however, requires mandatory criteria for drivers and privately-owned cars in order to guarantee the quality of service standards to the customers. The maximum driver's age is prescribed at 60 and 50 years for male and female drivers, respectively. Regardless of gender, every driver must be at least 22 years old and have a driving history of at least one year. Didi conducts a background check, reviewing the ID card, driver's license as well as insurance, driving and criminal records. Furthermore, a health test inspects whether drivers suffer from (mental) illnesses or are under the influence of illegal drugs or other restrictive medicaments (Didi Chuxing, 2019b). Private cars must fulfil the criteria of a quality inspection and have been purchased within the recent 6 years at a price of > RMB 70.000 (approximately USD 10.600)[13] (Didi Chuxing, 2019b). Didi's platform-specific requirements for private automobiles and drivers largely correspond to those of international competitors such as Uber (J. V Hall & Krueger, 2018; Didi Chuxing, 2019b).

2.4 Drivers socio-demographic characteristics

The most comprehensive study on the socio-demographic distribution of ride-hailing drivers in China is conducted by Didi Chuxing and the School of Labour

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[12] The Chinese government announced to tighten the regulation of ride-hailing services in consequence of two incidents, where passengers were murdered by drivers who obtained illegal access to the platform. The stricter regulation has been applied since January 2019 and requires licenses for both cars and drivers. Moreover, ride-hailing companies need to provide standards guaranteeing the safety of the passengers (Techcrunch, 2019; ChinaDaily,2018b). This thesis – however – empirically examines the period until 12/2017. Therefore, only the relevant regulation before January 2019 will be considered.

[13] The average USD-RMB exchange rate between 2008 and 2017 is approximately 1:6.6, respectively (Yahoo Finance, 2019). This average rate is applied throughout the thesis.

and Human Resources at Renmin University in 2017 (Didi Chuxing, 2017). A total of 30% of the entire driver base was randomly selected for a survey with a response of 30.671 active drivers in June 2017. Questionnaire answers are verified with data of the driver's respective app-generated behaviour. In addition, a data analysis covering all Didi-drivers on a provincial level provides insights into recent overall figures. In June 2017, 21,08 million people earned an income on the Didi platform, which accounts for 6.2% of the entire national third-industry workers (Didi Chuxing, 2017; NBS, 2019). The year-over-year number of Didi-drivers between 2016 and 2017 grew by 18,87% o.a. with a high variation among the 31 Chinese provinces. Inland provinces, such as Tibet, Xinjiang and Inner Mongolia showed the strongest accession, while 7 provinces (including Beijing and Shanghai) stagnated or decreased as exemplified in illustration 7. Illustration 8 shows a negative and significant ($p<0,01$) correlation of GRP and driver growth, indicating that in 2017 people in impecunious areas were disproportionally attracted by Didi, while regions with higher GRP are already mature (see Appendix II.). Point size represents the population quantity, which appears to be significantly positive related to driver growth. Additional figures point to the relevance of independent work on the livelihoods of low-income individuals: prior to joining Didi, 12% of drivers had been unemployed for over a year and 6,5% belong to families, with only one family member being employed and without other income sources except than Didi. The majority of drivers support family members: 83% are married (9 p.p. above the national average), and 86,7% have at least one child. The overall social dependency ratio suggests that the average driver must bear the financial burden of additional 1,65 family members (NBS, 2019).[14] Illustration 9 provides socio-demographic qualities of Didi-drivers: both, drivers (blue) and economically active population (grey) have a median age between 35-44. Yet, the distribution of drivers' age is right skewed and the standard deviation (SD or σ) is as 3 times as high as the equivalent of the overall population. 84% of the drivers are under the age of 44, compared to only 57% in the working age population. In

[14] The social dependency ratio compares the ratio of family members who earn any form of income to those who do not (e.g. due to school or retirement). The ratio is computed as follows: $Social\ dependency\ ratio = \frac{\text{total number of household members – household members with income}}{\text{household members with income}}$.

Driver growth at provincial level

Hongkong, Macao and Taiwan excluded, (2016 vs. 2017 YOY, %)

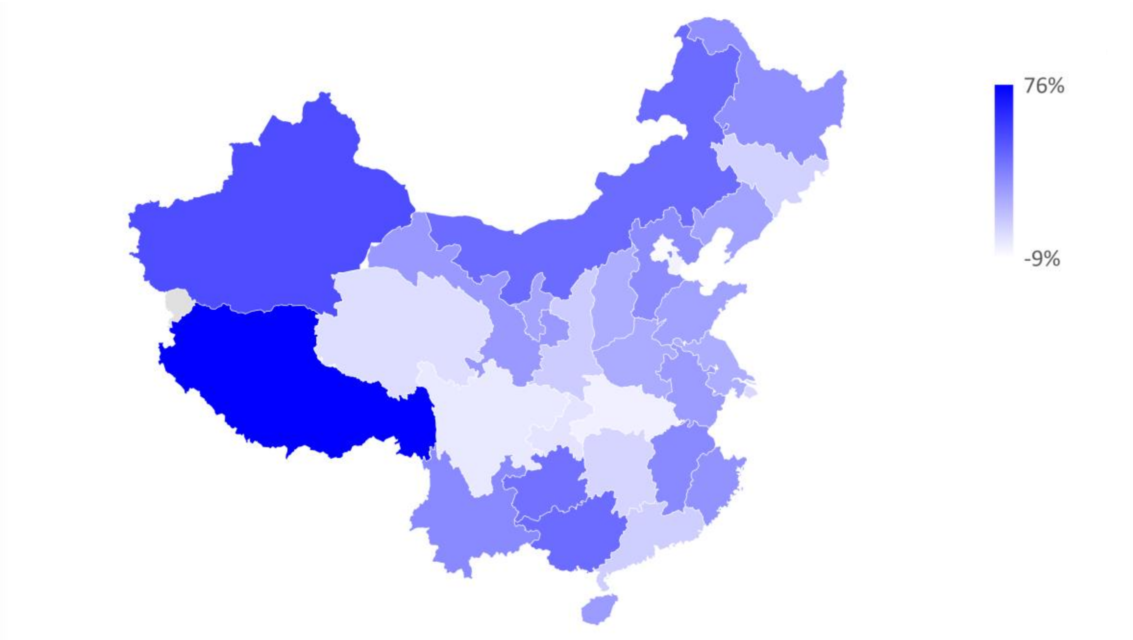

Illustration 7: Driver growth at provincial level (own illustration, data from Didi Chuxing, 2017).

Provincial driver growth vs. gross regional product (GRP)

China, (2016 vs. 2017 YOY, %, GRP=2017)

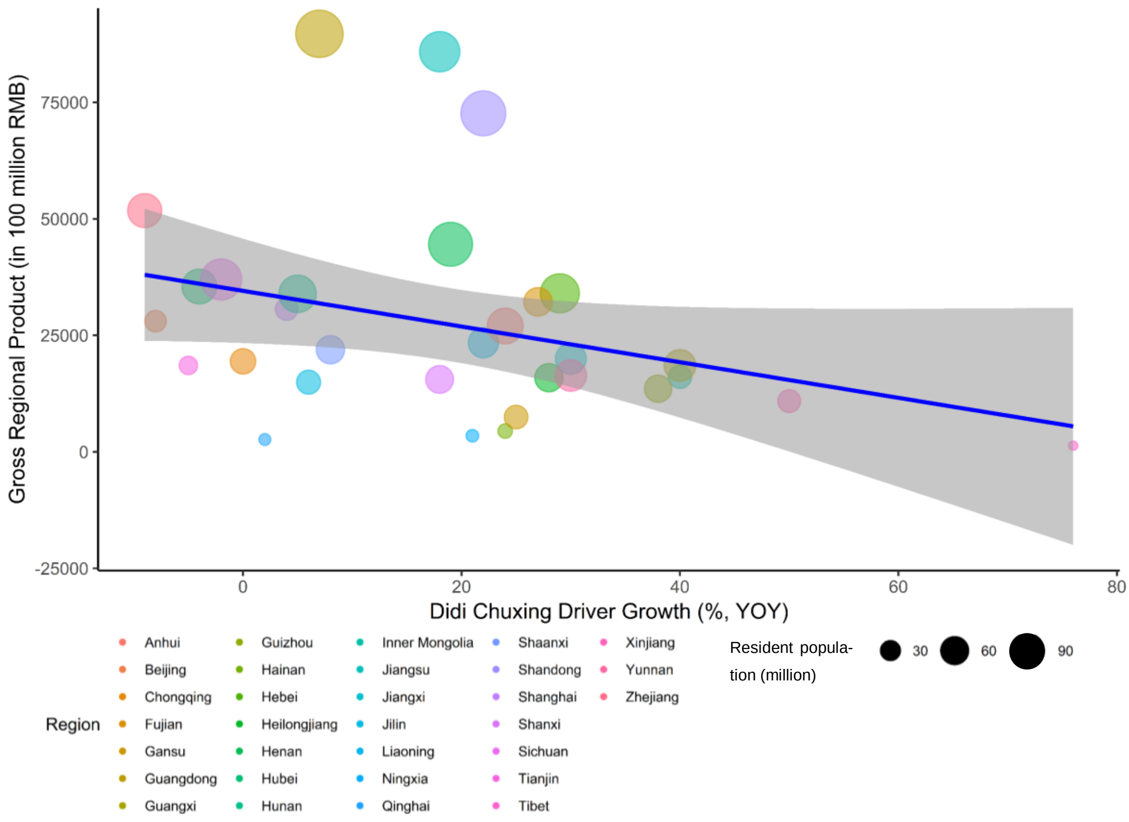

Illustration 8: Provincial driver growth vs. GRP (own illustration, data from Didi Chuxing, 2017).

addition, the SD indicates a stronger discontinuity in the age distribution of drivers. However, except for a shift to the Millennials, the graph exemplifies that the age distribution roughly follows the overall economically active population, suggesting a widely absence of age discrimination. In contrast, 92% of drivers are male, although the corresponding proportion in society is only 51%. Working as a driver seems to be fundamentally less appealing for woman, as an equally small proportion has been investigated in other ride-hailing services as well as in the conventional taxi industry (J. Hall & Krueger, 2018). The level of education shows a comparable SD between drivers and total society, but the driver's distribution is left-skewed. Although it is not a prerequisite for this type of occupation, surprisingly many drivers own a university degree. In fact, the proportion of drivers with a university degree is 120% higher than the share of academics in the entire soci-

Socio-demographic characteristics of Didi drivers

China, (Q2/2017, %)

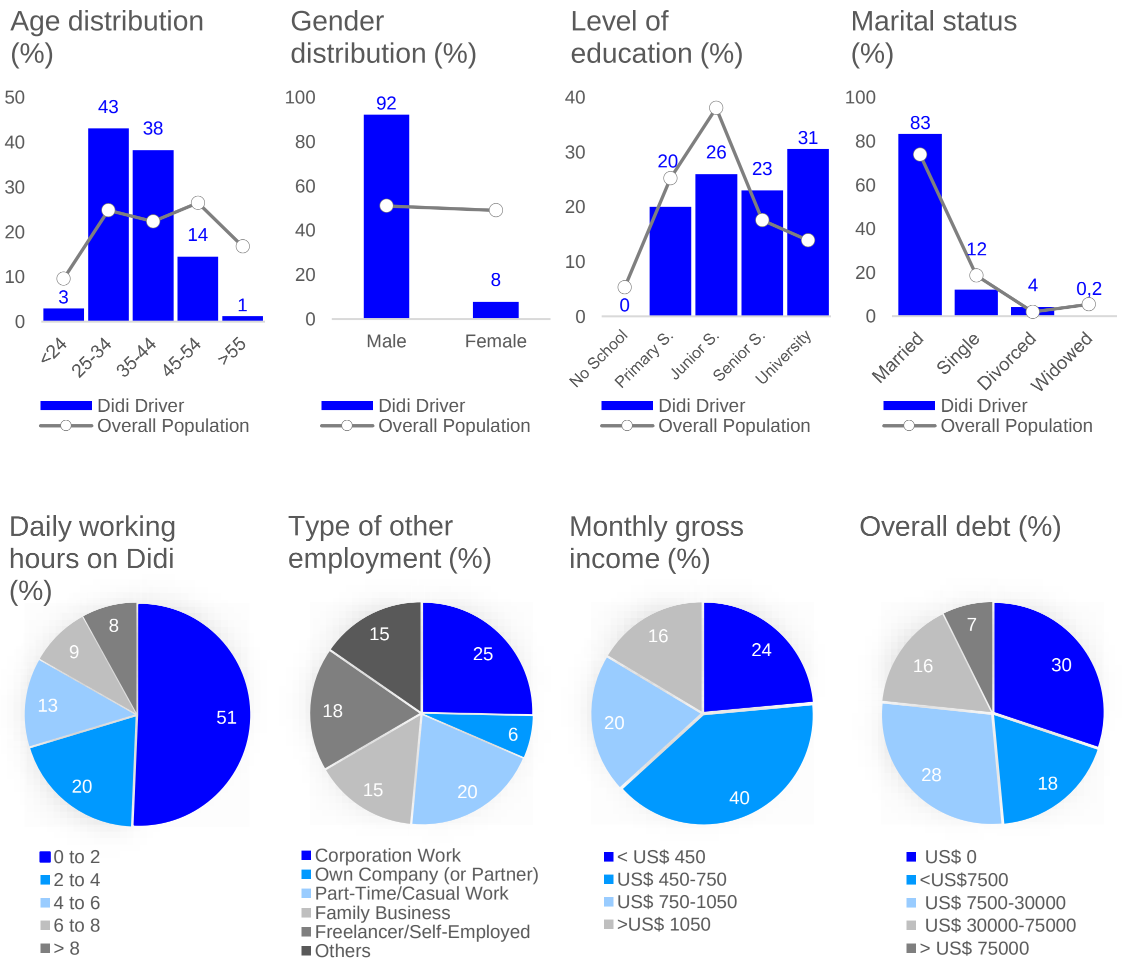

Illustration 9: Socio-demographic characteristics of Didi drivers (own illustration, data from NBS, 2019; Didi Chuxing, 2017).

ety. Nevertheless, the low SD of Didi-drivers across the educational categories indicates, that educational attainment is not a job barrier.[15] 51% of Didi-drivers work less than two hours a day on average. The flexibility of e-hailing seems to make Didi attractive as a second or part-time job, which corresponds to similar results from previous studies (J. Hall & Krueger, 2018; The Aspen Institute, 2016). Among the drivers with other employment besides Didi, no occupational form dominates significantly. But with 25,3% most of the drivers are employed in corporations. Combined, 45,3% of drivers work in corporations or part-time, and the majority in the 3rd industry strata. The service sector accounts with 46,6% for almost half of all drivers with an additional job, while 25,6% work in manufacturing industries. When asked about their motivations to join Didi, 62% felt that their original incomes were too low, while 47% joined because they had too much idle time. A further 16,3% stated the risk of dismissal in their primary job as primary intention. Drivers monthly gross income presents the distribution of overall income (including earnings via the Didi-platform). 84% of the drivers earn less than the average monthly salary across all sectors of employees in urban areas (NBS, 2019). In addition, drivers earn an average of 50% of their total income on the Didi platform (Didi Chuxing, 2017; NBS, 2019). A majority of 70% of drivers is confronted with debts. These figures illustrate the paramount importance of flexible income sources in China, especially for low-income individuals and families. Hourly income depends on the driver's rating since Didi's matching algorithm preferably allocates trip requests to the highest-rated drivers. Nevertheless, hourly income, in general, is independent of total hours worked – which is again a similarity to other e-hailing services such as Uber (J. Hall & Krueger, 2018).

2.5 Users socio-demographic characteristics

The users' age distribution seems closer to the drivers' characteristics than to the overall society: young users dominate with a median age of 25-34 and a proportion of 78,8% with an age of less than 44 years, respectively. However, the sex

[15] Despite the suggestions of independence from higher education, obtaining a driving license is a strict barrier. This circumstance explains why there are no drivers without any school education. The 5% share of uneducated citizens could be a result of turbulences during the Cultural Revolution (1966-1976) since compulsory schooling was already introduced in 1928 (Glöckner, 2013).

ratio hardly differs from the total population. An eminent contrast to the unilateral distribution of drivers, suggesting that the use of ride-hailing is independent of gender. The most prevalent users are prosperous individuals, according to the distribution of usage by income levels. Nevertheless, 58,5% of customers obtain only a medium or small disposable income. Thus, the service appears to be affordable even for impecunious parts of society. The described distributions are reflected by illustration 10.

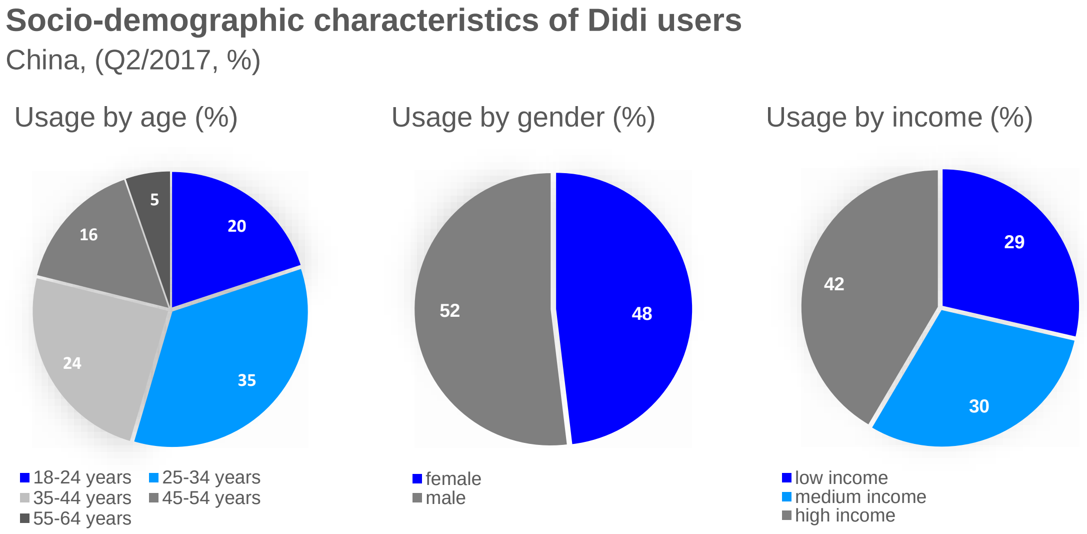

Illustration 10: Socio-demographic characteristics of Didi users (own illustration, data from Statista, 2019b).

3 Literature review and development of research hypotheses

3.1 Preliminary note

With its inception in 2009, the concept of ride-hailing exists for merely a decade (Chang, 2017; J. Hall & Krueger, 2018; Kashyap & Bhatia, 2018). However, there has been a long stream of literature examining its various externalities, including the disruption of traditional industries and the displacement of incumbents (e.g. Berger, Chen, et al., 2018; B. N. Greenwood & Wattal, 2015; J. V Hall & Krueger, 2018; Park et al., 2017; Vallas, 2018). By reviewing relevant literature concerning implications on prices, employment and wages, this section will evolve the argumentation to define the research hypotheses.

3.2 Hypothesis 1: decline of consumer price levels for individual mobility

Internet-facilitated services have proven to tremendously reduce consumer costs in numerous areas. Extensive and costly search times and information asymmetries, for instance, have been vastly diminished by the invention of Google search and GPS navigation provided to consumers at no charge (Hesseldahl, Ballan, & Wendt, 2016; Jolivet & Turon, 2018). A substantial proportion of the disruptive potential of ride-hailing services derives from its capability to mobilize underutilized capacities and to provide a flexible supply via an app-based digital product design. This becomes particularly obvious when comparing the economic efficiency of e-hailing with its most conspicuous competitor – the traditional taxi industry. The matching mechanism connecting passengers and drivers of ordinary taxicabs is typically based on a two-way radio dispatch system developed in the 1940s or relies on spontaneous sight-based street hailing (Cramer & Krueger, 2016). In contrast to this traditional technology, several researchers point to the efficiency advantages of app-based matching algorithms deployed by ride-hailing services (Buchholz, 2018). By processing GPS information from the driver's and user's smartphones, algorithms largely reduce searching and waiting times (Cramer & Krueger, 2016; X. Wu & Zhi, 2016), uncertainty and inconvenience of waiting due to real-time mapping (Jin, Kong, Wu, & Sui, 2018), substitute dispatch centres (Jin et al., 2018) and allow for a greater supply of rides per time unit (Yaraghi & Ravi, 2017). Thus, transaction costs are reduced and recourses are effectively allocated (Deighton-Smith, 2018). With account-based user profiles, the digital product design facilitates the operational processes, such as the automatic transfer of payments via the user's smartphone (Deighton-Smith, 2018). In addition, ride-hailing companies exploit the app-generated real-time information on overall passenger demands and driver supply. While taxi fares widely remain constant regardless of market demand, ride-hailing corporations apply dynamic "surge" pricing. The basic price structure, similar to a taxicab with a minimum fare and a supplement according to distance, is amplified by a tailored dynamic pricing mechanism, which reflects demand fluctuations throughout the day and increases in peak hours (Edelman & Geradin, 2015; Zoepf, Chen, Adu, & Pozo, 2018). As a result, the algorithm allocates scarce labour supply during peak hours to customers with the highest marginal rate of substitution, thereby, maximizing social welfare (Arrow, 1972). Moreover, the comprehensive market information allows predicting demands with a disproportionally larger accuracy than the "offline" taxi businesses. For instance, Didi claims its artificial intelligence (called "Didi-brain") to predict volume and location of demands in the next 30 minutes with an accuracy of 85%, processing 4875 TB of data per day, covering traffic status, as well as users' and drivers' behaviour (Didi Chuxing, 2019c). However, predicting future demands accurately is worthless in case capacities are surpassed and limited by license restrictions – a significant issue in the taxi sector, as exemplified in section 2. Ride-hailing corporations benefit from two competitive advantages, which substantially counter the supply-bottleneck: on the one hand, the flexibility of surge pricing increases the net salary of drivers during peak periods, stimulating rapid supply responses to excessive demand (Cramer & Krueger, 2016). Several studies examining labour supply elasticities associated to surge pricing confirm its effectiveness to increase the supply of rides (M. K. Chen & Sheldon, 2015; J. Hall, Kendrick, & Nosko, 2015). On the other hand, e-hailing drivers face comparably low market barriers due to liberal regulative criteria (see section 2). An important advantage, since flexible part-time work becomes economically viable (Deighton-Smith, 2018). In consequence, flexible e-hailing drivers leveraging private cars can achieve higher capacity utilization rates compared to taxi drivers working with single-purpose vehicles throughout slow and busy times of the day (J. Hall & Krueger, 2018; Yaraghi & Ravi, 2017). Divergent policy requirements within the mobility sector are part of a broader discussion with several scholars arguing for economic benefits through a deregulation of the industry's obsolete or inappropriate constraints. *Moore & Balaker (2006)* illustrate how heavily regulated taxi industries are manipulated by incumbents for their benefit, to the cost of passengers and drivers. Considering the driver's perspective, *Gloss, McGregor, & Brown (2016)* exemplify, that only 29% of New York's taxi-drivers are medallion-owners, while 71% are self-employed but forced to pay rental fees for the right to drive. The system, originally implemented to constrain supply and guarantee a decent living standard for drivers, now puts additional pressure on incumbent livelihoods. With a focus on passenger expenses *Abelson (2018)* estimates the gains from an unrestricted taxi market in Sydney at USD 265 million per annum. This illustrates how regulative costs can significantly increase taxi fares (Deighton-Smith, 2018) and rigid supply restrictions harm the flexibility of taxi companies, resulting in poor productivity and occupation rates (Chang, 2017; Cramer & Krueger, 2016).[16] *Cramer & Krueger (2016)* estimate the mismatch of occupancy rates between Uber and taxi drivers in five major US-cities: their findings suggest, that on average UberX drivers spend a 30% higher fraction of time and drive a 50% higher proportion of miles transporting passengers compared to taxi drivers. When further examining the average price implications of these utilization advantages, they concluded, that Uber-drivers can charge 28% less than taxicabs while still generating the same hourly revenue (Cramer & Krueger, 2016).[17] With reference to several authors, the above-illustrated arguments indicate a price advantage of e-hailing services compared to ordinary taxicabs (Chang, 2017; Conway et al., 2018; Cramer & Krueger, 2016; Jin et al., 2018). Considering the increasing fraction of e-hailing

[16] Regulation can also increase passenger safety and convenience of a service through standardization as described in *Cramer & Krueger (2016)*. *Gloss et al. (2016)* for instance, provide a description of industries, where – in turn – deregulation have led to a deterioration of consumers' and workers' benefits. However, this section focusses on regulation of the taxi industry, which is critiqued by several authors as inappropriate or obsolete.

[17] The computation of *Cramer & Krueger (2016)* ignores fixed costs and covers only a limited number of cities. Therefore, the findings should be viewed as suggestive. Due to the scarcity of available data very limited studies on the capacity utilization of e-hailing services exist.

in the daily mobility in China (as examined in section 2), implications on the overall average mobility costs are likely. Building on the described argumentation, this paper raises the following assumption:

Hypothesis 1: Didi Chuxing's growing popularity within a certain province decreases the average price level for personal mobility.

3.3 Hypothesis 2: empowerment of employment in the mobility sector

In addition to potential impacts on consumer prices, the rapid adoption of ride-hailing services is likely to have perceptible effects on labour markets. Detailed figures documented in section 2 exhibit, how e-hailing platforms draw on enormous numbers of agile and independent labour to fuel their expansion. One interesting question is, whether these rental marketplaces simply displace existing occupations or actually extend available work opportunities – whether ride-hailing is a supplement or substitute for incumbent jobs (Berger, Chen, et al., 2018; Kenney & Zysman, 2016). Proponents argue that the technological innovation potentially formalizes a previously less developed industry, thereby, stimulating the overall market growth and job creation (Berger, Frey, Levin, & Santosh, 2018; J. Hall & Krueger, 2018). Critics highlight threats to existing providers in exposed sectors. The innovation might destroy disproportionally more work than it creates, putting pressure on the working conditions of incumbent jobholders (Chee, 2018; Gloss et al., 2016; Vallas, 2018). While labour substitution by technological innovation is predominant in the 1st and 2nd industry strata (Decker, Fischer, & Ott, 2017), employment in the service sector might be flourished by the complementary nature of work between humans and technology (Card & DiNardo, 2002). For instance, *Bessen (2015)* deduces an increase in the aggregate number of bank tellers, despite the diffusion of automated teller machines (ATM's). Store-individual labour displacement by low-cost ATM's turned out to be offset by the corresponding cost reduction for the opening of new bank branches; thereby, a disproportional launch of new locations actually increased the total demand for bank tellers (Bessen, 2015). Regarding the ride-hailing sector, empirical work emphasizes a supplemental power. Studies of the US market suggest, that ride-hailing services particularly compensate spatial and temporal supply-demand imbalances during the commuting periods (e.g. Z. Li, Hong, & Zhang, 2017). *Dong, Wang, Li, & Zhang (2018)* confirm the findings with data from Didi Chuxing in Beijing, China. Counterintuitively, the traditional taxi sector as apparent substitute grows in overall market size – despite the entry of a ride-hailing service (Conway et al., 2018). *Berger, Chen, et al. (2018),* for instance, identify a staggered expansion of self-employment after the market entry of Uber in the 50 largest metropolitan areas. However, the effect does not suspend the incumbent sector: while the number of self-employed drivers increases by 50% o.a., traditional taxi drivers show a complementary rise by 10% c.p.[18] *Conway et al. (2018)* demonstrate how the advent of e-hailing has expanded the for-hire vehicle travel, which doubled in size between 2009 and 2017. With regards to public transit, *J. D. Hall, Palsson, & Price (2018)* investigate an increase of passenger traffic by 5%, two years after the first market entry of ride-hailing services. Findings from an investigation by *Z. Li et al. (2018)* on the interactions between Uber's local market introduction and the labour market in 164 US cities indicate a decline in the unemployment rate and an increase in labour force participation through the activity of e-hailing services. *Kashyap & Bhatia (2018)* confirm the creation of viable employment opportunities with data from the Indian ride-hailing service Ola. The data reviewed in subsection 2.4 provides further evidence: 12% of the drivers had been unemployed for over a year prior to joining Didi. Moreover, the platform offers an important work alternative to absorb large quantities of the surplus labour force, e.g. from the coal and steel industry. A static regression illustrates a negative correlation between driver growth and unemployment rate amongst the 31 Chinese provinces (Didi Chuxing, 2017).[19] The results of these investigations contribute to the wider assumption that the advent of the SE empowers employment (B. Fang, Ye, & Law, 2016; Z. Li et al., 2018; Mäkinen, 2006; X. Wu & Zhi,

[18] Although the findings indicate an absence of negative impacts on aggregate employment of incumbent workers, salary levels are affected: According to *Berger, Chen, et al. (2018)* and *Chang (2017)*, the average revenue of ordinary taxi drivers declined by 10% and 18% after the entry of Uber in the US and Taiwan, respectively.

[19] *Didi Chuxing (2017)* utilize official unemployment rates, whose explanatory power is limited as reviewed in subsection 4.4. Thus, the findings should only be viewed as suggestive.

2016). But what underlying causes induce this effect? A growing body of literature suggests both low entry barriers and high working flexibility, which facilitate labour market adjustments in response to innovative technological developments (Berger, Chen, et al., 2018; Cramer & Krueger, 2016; Gloss et al., 2016; Vallas, 2018). In addition to the aforementioned liberal regulation, some effects become visible in the descriptive driver analysis, provided in subsection 2.4. For instance, widely independence of age and education among the drivers, as well as moderate asset requirements when individuals exploit existing commodities or renting options.[20] At the same time, ride-hailing services offer drivers versatile flexibility in managing their individual working schedule. This encourages more than half of the drivers to work in part-time. However, the two-sided composition of digital ride-hailing markets creates a massive network of peers, which in turn increases the likelihood of corresponding demand to the flexible capacity supply (Mäkinen, 2006; J. Song & Walden, 2011). Ride-hailing services thereby promote a viable work alternative for people who struggle in the competitive labour market or are unable to work in the fixed time schedule of a conventional nine-to-five job, such as stay-at-home parents, students, and retirees (Collier, Dubal, & Carter, 2017; Eisenmeier, 2018; Z. Li et al., 2018). With reference to the discussed literature the following hypothesis is developed:

Hypothesis 2: Didi's expanding activity in a certain province increases the employment in the transportation sector relative to overall population and proportion of economically active residents.

3.4 Hypothesis 3: rising earnings in cross-industry low-income sectors

A majority of studies in the SE-context is centred on effects of an emerging innovation and a respective incumbent industry, whose value creation is regarded as

[20] Little evidence exists on detailed proportions of for-hire vehicles in the Chinese e-hailing sector. However, two arguments support a proportion of approximately 50% in China: *Eisenmeier (2018)* reports a share of 60% of drivers who do not possess the car they drive in Mexico (Eisenmeier, 2018). The GDP per capita between China and Mexico differs only by 0,85% (Worldbank, 2019c), which could indicate a similar proportion. This hypothesis is supported by case-study reports (e.g. *Towson, 2018*), who point to a proportion between 50-60% of for-hire cars. The proportion could be slightly higher as Didi significantly supports drivers when purchasing a car (e.g. with financing options or special purchase discounts from cooperating vehicle manufacturers) (Guo et al., 2018).

a substitute, e.g. Airbnb versus the hotel sector or Uber against the taxi business (Berger, Chen, et al., 2018; Chang, 2017; Guo et al., 2018; Zervas et al., 2013). However, productivity alterations as discussed in subsection 3.2 are likely to cause additional cross-industry implications. *Balassa (1964)* and *Samuelson (1964)* explain remuneration effects by intersectoral disparities in productivity innovations between tradable and non-tradable goods (known as Balassa-Samuelson-effect). Since tradable goods compete in larger (global) markets, industries are apt to respond to productivity innovations. In contrast, labour-intensive non-tradable goods only compete in a local market (e.g. hairdresser), therefore, the sector's efficiency remains prevalently constant. Assuming the compensation to equal the marginal revenue product of labour, wage standards increase in the tradable goods sector but are offset by the productivity growth. However, to prevent a transition of labour supply, the non-tradable sector is obliged to equalize wage levels with the more efficient tradable goods sector, although productivity levels of the former remain detached.[21] Generalized to divergent efficiency gains among industry sectors, the Balassa-Samuelson-effect theoretically formulates intersectoral occupation transition and/or compensation adjustments in low-productivity sectors. As illustrated earlier, ride-haling services achieve perceptible efficiency increments through the deployment of innovative technology. Considering the sector's characteristics, an occupation switch could be particularly attractive for two types of workers: (1) by offering high autonomy and flexibility, ride-hailing attracts individuals who work independently by choice (Manyika et al., 2016) and report higher levels of life satisfaction due to the characteristics of flexible employment (Berger, Frey, et al., 2018). (2) Besides intrinsically motivated individuals, promising job opportunities have proven to cause an occupational change of extrinsically motivated employees (Martin, 2018; Triandis & Herzberg, 2006). From this perspective, Didi's business opportunity becomes lucrative for potential drivers, as soon as the expected income surpasses the level of current occupations (Mumtaz & Hasan, 2018) or the individual labour supply is more ef-

[21] A description of empirical verifications of the Balassa-Samuelson effect is provided in *Tica & Družić (2006)*.

ficiently exploited considering socio-demographic qualities such as age or education (Morgeson, Reider, Campion, & Bull, 2008; Stuhlmacher & Walters, 1999). After deducting platform commissions and vehicle expenses[22], estimations of the hourly income of e-hailing drivers vary from an average of USD 13,03 to 14,97 in the US, a median of USD 15,01 in the UK (London) and a global average of USD 6,80 (Statista, 2019d; J. Hall & Krueger, 2018; Berger, Frey, et al., 2018; Burgstaller et al., 2017). Comparing each value to average hourly earnings in the respective country, certain proportions of the economically-active population are potentially addressed: the US estimation surpasses the average hourly income of ordinary taxi drivers (USD 12,56), and the 25th percentile mean across all sectors and occupations (USD 12,37) (BLS, 2019; J. Hall & Krueger, 2018). The estimated hourly earnings in the UK surpass the 25th percentile median across all industries and occupations (USD 13,66) (Berger, Frey, et al., 2018). In the case of China, detailed examinations are unavailable. However, the survey data analyzed in subsection 2.4 provides static gross monthly average incomes from the year 2016 (Didi Chuxing, 2017). Contrasted to average pre-tax wages in urban areas provided by the NBS, driver's gross income corresponds to 62% of the arithmetic mean across all industries (see Appendix V. for the underlying assumptions) (NBS, 2019). This could result in a similar cross-industry transition of low-income workers, causing a drop of labour supply for low-skilled jobs in incumbent industries as described by the Balassa-Samuelson effect. In other words: the viable working opportunity emerged by the rapid adoption of e-hailing services potentially decreases the labour supply in low-income occupations. In response to fluctuations and fierce competition for available labour, companies,

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[22] Detailed figures on the net revenues from ride-hailing drivers are difficult to obtain. Estimations of the individual vehicle costs are complex, since they vary with car model, driving style, traffic situation and other factors such as tax relevant deductions. The cited references use different approximations to investigate the costs: *Hall & Krueger (2018)* combine per-mile cost figures from the American Automotive Association (AAA) on gasoline, maintenance, depreciations, rental fees, and insurance with average driving miles of Uber drivers. The authors exclude fixed costs (depreciations, insurance and registration fees) for part-time drivers, since these costs will also apply when the car is used for private purposes. The resulting hourly earning estimations amount to USD 17,41-19,35 with vehicle costs of USD 4,38 o.a. *Berger, Frey et al. (2018)* combine self-estimated computations by Uber drivers with independent vehicle-level data, following an equal approach as *Hall & Krueger (2018)*. They report earnings of USD 21,79 and subtract an amount of USD 6,78 for vehicle expenses. Burgstaller et al (2017) report earnings of USD 12,3 and deduct average vehicle costs and commission fees of 45%. The given figures are arithmetic means of the number of hours worked (part-time vs. full time), thus, should be viewed as suggestive.

dependent on the supply of low-skill/low-income individuals, would have to increase salaries in order to stay competitive in the labour market. In turn, a perceptible shift in average salary levels of low-income industries after the market entry and sprouting adoption of ride-hailing services is likely. Drawing on this line of argumentation the following hypothesis is formulated:

Hypothesis 3: Didi's expanding activity within a certain province increases the wage level of individuals in cross-industry low-income sectors.

4 Data, econometric strategy, and descriptive results

4.1 Data sources

In order to test the described hypotheses, this paper utilizes different types of data sources, each of which is most suited to expose the suspected effects. Each hypothesis draws either on aggregated macroeconomic or microeconomic survey data (labour, price or salary levels, respectively) as well as a variable to approximate the activity of Didi within a province. First, aggregated data on prices, employment and socio-demographic population characteristics are gathered from the National Bureau of Statistics China (NBS). The NBS reports a variety of data in an annual sequence for the 31 Chinese provinces.[23] Since the earliest Didi entry was in 2012, data from 2008 to 2017 are evaluated to balance pre- and post-entry periods. Second, data from the China Family Panel Studies (CFPS), conducted biennially by the Institute of Social Science Survey at Peking University, is analyzed to draw a more sophisticated conclusion. The CFPS is a longitudinal social survey, designed to investigate economic activity, educational attainment and family dynamics in China. It consists of approximately 35.000 nationally-representative participants from 25 provinces, representing 95% of the Chinese population (CFPS, 2019). This thesis utilizes the waves of 2010 and 2016. Each hypothesis processes different figures as described in subsection 4.3, 4.4 and 4.5. In most cases, Didi launches its service in specific cities rather than in an entire province. However, most parts of the analyzes in this research are conducted at provincial level, since (1) macroeconomic figures on labour market and price developments are only available at provincial level and (2) the granularity of data gathered from NBS allows to exclude individuals from rural areas, thereby, estimations are limited to relevant urban zones. Since corporate information is rather limited or static, estimating the proliferation of Didi, i.e. the usage rate and number of drivers, requires an alternative approach. Estimations based on search engine volume have previously demonstrated to predict consumer be-

[23] including Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang.

haviour and price developments more accurately than conventional indicators (Carneiro & Mylonakis, 2009; Choi & Varian, 2012; L. Wu & Brynjolfsson, 2012). Converted to the ride-hailing sector *J. Hall & Krueger (2018)* and *J. D. Hall et al. (2018)* demonstrate that the number of Uber drivers and the respective regional Google search volume (with the keyword "Uber") are significantly positive correlated (see Appendix III.). Several authors confirm the adequacy of search volume to accurately predict the prevalence of ride-hailing services in empirical studies (Berger, Chen, et al., 2018; Z. Li et al., 2018). Since Google is restricted in China, this paper surveys trend-data from the Chinese search engine Baidu to measure Didi's attendance intensity. Baidu is chosen due to its large market penetration in China (>80% of the total search volume) and the possibility to spatially cluster the results at provincial level (Statista, 2019c). With a focus on the Chinese market, recent literature validates the aptitude of Baidu Index to forecast diverse variables of interest, such as consumer behaviour, stock returns and tourist volume (J. Fang, Wu, Lu, & Cho, 2017; X. Huang, Zhang, & Ding, 2017; Shen, Zhang, Xiong, & Zhang, 2017). Comparative studies, examining several search engines, suggest that Baidu Index reaches the highest predictive accuracy in China (Vaughan & Chen, 2015; X. Yang, Pan, Evans, & Lv, 2015). Using the keyword "Didi Chuxing/Dache", the daily average search volume for each of the 31 Chinese provinces is generated in an annual sequence from 2008 to 2017. Since Baidu Index is not publicly available, the data has been collected using web-scraping techniques (see Appendix IV.). A feasible way to examine the approximating adequacy of Baidu Index is to compare the search volume of 2016 with static figures released by Didi in the same year (Didi Chuxing, 2017). Didi reports Guangdong, Zhejiang, Jiangsu, and Sichuan as provinces with the most active drivers. Drawing on the 2016 magnitude of Baidu Index searches, the provinces rank among the top 5 (with Beijing in addition); when comparing the arithmetic mean over the period 2008-2017, they are among the top 6 provinces (with Shandong and Beijing in addition). Building on the aforementioned literature, this is a strong indicator that Baidu Index is a suitable proxy to estimate the activity of Didi within a certain area. However, the accuracy is at risk as Baidu searches are not always zero before Didi enters a province. Non-zero search results in regions, where Didi is (still) unavailable, can indicate curiosity for the service. But since ride-hailing is not a viable option in there, impacts on prices, labour and wage-levels cannot reasonably be explained by search volume. As a result, non-zero searches potentially bias the accuracy of estimations. This paper alleviates this concern by combining Baidu Index with a dichotomous market entry variable which is generally 0 and becomes 1 when Didi enters a province i at time t. The market availability of Didi in the covered 31 provinces has been investigated by a comprehensive web-media analysis with a focus on capital cities (e.g. advertisement and press materials) and information provided by Didi. Applied as an interaction-term ($Baiduint_{i,t}$), Baidu Index and the market entry dummy allow for an unbiased estimation.

4.2 Econometric identification

This thesis proposes a two-way (fixed/random-effects) panel regression model to investigate empirically whether price, labour and intersectoral salary indicators are affected by the market activity of Didi within China. This research design appears suitable, as it effectively controls for area static heterogeneity and time fixed-effects (such as unobserved temporal trends or shocks) (Allison, 2012; Wooldridge, 2015). The approach differs from comparable studies such as *Berger, Chen, et al. (2018)* and *Z. Li et al. (2018)* which conduct a natural experiment to systematically assess the impact of Uber on labour markets and salary levels of taxi drivers. The authors of the abovementioned papers favour a multi-side-entry difference-in-difference approach because Uber's temporal market launches into metropolitan statistical areas vary in time. The likelihood of estimation distortions due to unobserved general trends decreases when various temporal moments are evaluated, and the assumption of (partial) statistical independence among areas holds. This, in turn, allows for a more profound contrast between treatment and control observations (Dunning, 2008). Although Didi gradually expanded in the Chinese provinces between 2012 and 2015, the current core business model was introduced simultaneously across all available provinces in early 2014 (J. Y. Chen, 2018). At this time, Didi was attendant in 30 provinces accounting for 99,8% of the Chinese population (NBS, 2019). Consequently, varying market launches are not likely to enhance the causal conclusions in the case of Didi. This paper addresses the described concerns by examining endogenous trends prior to the analysis in order to identify and control for possible effects. Moreover, some model assumptions are verified in a sensitivity analysis (e.g. placebo test) to allow a causally valid explanation of the phenomenon. *Fang et al. (2016)* and *L. Song & Winkler (2014)* exemplify the aptitude of fixed- and random-effects regression models in the research context. An extension to the referred papers is applied in this thesis, aiming to additionally consider dynamic natures within the time-series. Such effects could result from potential deferrals between the expression of interest for the service (as manifested in the magnitude of Baidu search volume) and the actual use of Didi by customers and drivers (which in turn affects indicators as argued in *hypothesis 1-3*). Hence, a one-period weighted distributed lag of the explanatory variable is incorporated in the model, considering the interest expression in $t-1$ when estimating the suspected effects in period t. The general unobserved model estimated in this thesis is given by *equation (1)*:

$$Y_{i,t} = \beta_1 * Baiduint_{i,t} + \beta_2 * Baiduint_{i,t-1} + \vartheta_s * \mathbf{X}_{\boldsymbol{i,t}} + \theta_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

In this equation, the dependent variable Y represents the accordant response variable of interest (as described in subsection 4.3, 4.4 and 4.5), i denotes a certain province, t a time period, β_1 depicts the coefficient of $Baiduint_{i,t}$, and β_2 the coefficient of the one-period distributed lag $Baiduint_{i,t-1}$. ϑ_s represents the coefficient to determine the effect of control variable s, from set $\mathbf{X}_{\boldsymbol{i,t}}$ of control variables, θ_i depict the regional time-invariant heterogeneity (which can also be regarded as the unknown intercept of entity i) and γ_t the respective time fixed-effects. Eventually, $\varepsilon_{i,t}$ is the random error term.

4.3 Quantifying implications on price levels

The NBS provides annual consumer price indices in a granularity, enabling a detailed evaluation of interactions between passenger transport prices and expanded ride-hailing mobility options. The collected panel data set covers the progress throughout the years 2008-2017 in all 31 provinces, thereby accounting for 310 observations per variable. The model deploys the consumer price index for the category "transport" ($CPI_{i,t}^{T}$) as dependent variable, whose development is expected to be negatively affected by the intensity of Didi Chuxing as independent variable ($Baiduint_{i,t}$). However, certain alternative factors such as public transit are likely to influence the price index. Hence, the model incorporates control variables to isolate the effect of ride-hailing, i.e. the fuel price development to control for deviations in the resource costs ($fuelprice_{i,t}$), the amount of passenger traffic to balance changes in mobility demands ($pass.traffic_{i,t}$), and the public transportation price to eliminate impacts from public transportation variances ($publictransprice_{i,t}$). In anticipation of the detailed discussion in subsection 4.6, the economically active population ($EAP_{i,t}$) and internet penetration ($IP_{i,t}$) are integrated into the model to prevent endogenous confounding. Using mathematical notation, the unobserved model specifying *hypothesis 1* is given by *equation (2)*:

$$\begin{aligned} CPI_{i,t}^{T} &= \beta_1 * Baiduint_{i,t} + \beta_2 * Baiduint_{i,t-1} + \vartheta_1 * fuelprice_{i,t} + \\ &\vartheta_2 * pass.traffic_{i,t} + \vartheta_3 * publictransprice_{i,t} + \vartheta_4 * EAP_{i,t} + \\ &\vartheta_4 * IP_{i,t} + \theta_i + \gamma_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $fuelprice_{i,t}$ and $publictransprice_{i,t}$ are transformed into an index and together with $CPI_{i,t}^{T}$ adjusted to the base year 2008 (2008=100). In addition, $pass.traffic_{i,t}$, $Baiduint_{i,t}$ and $Baiduint_{i,t-1}$ are log-transformed[24] to facilitate the interpretation of the estimates (Benoit, 2011). $EAP_{i,t}$ and $IP_{i,t}$ represent the percentage of society within a province i, corresponding to the working age of 16 to 64 years or with access to the internet, respectively.

4.4 Quantifying implications on employment

As a key indicator of labour market dynamics, *Z. Li et al. (2018)* evaluate unemployment rates with reference to the market entry of ride-hailing services. However, this indicator is not suitable for an estimation in China, due to several deformations in its computation by the government agencies. Official statistics are

[24] Log-transformation using natural logarithm (ln) generally requires positive values (Ekwaru & Veugelers, 2018). However, the data structure includes genuine zeros in the period prior to Didi's activity. To prevent distortions in the transformation, a constant c with a magnitude of 1 is added to each zero prior to transformation ($\ln(BIS = 0_{i,t} + (c = 1))$). The constant $c = 1$ is particularly suitable since log-transformation exactly outpace the adjustments (ln(1) = 0).

surprisingly stable[25], exceptionally low, and uncorrelated to GDP. Unique characteristics, making the country an abnormal outlier from economies of comparable development and size (Feng, Hu, & Moffitt, 2017; Worldbank, 2019d; NBS, 2019).[26] Thus, it is unlikely that the unemployment rate accurately reflects labour market dynamics as argued in *hypothesis 2*. This paper builds on an alternative approach by *Fang et al. (2016)*, who analyze variation in the number of employed workers in sectors facing an increasing activity of sharing economy platforms. With respect to the ride-hailing business in China, the number of urban self-employed individuals in transport, storage and post ($NSP_{i,t}^{TSP}$) seems promising to isolate the effect as dependent variable[27]. The indicator provided by the NBS particularly corresponds to the characteristics, since (1) state-owned enterprises (SOEs) are excluded, which largely dominate the (irrelevant) aviation, railway and postal industries (Gang & Hope, 2013; Macintosh et al., 2018), (2) in contrast to the SOE dominated sectors, self-employment is the prevailing organization in the ride-hailing business (Didi Chuxing, 2017; Mengkui, 2014), (3) distracting fluctuations within incorporated private industries (e.g. taxi business) can be controlled effectively. Similar to *equation (2)*, the model estimates the activity of Didi by the explanatory variable $Baiduint_{i,t}$, whose expanding intensity is expected to significantly increase $NSP_{i,t}^{TSP}$. Further control variables are included as follows in order to accurately isolate the effect of ride-hailing drivers: *Berger, Chen, et al. (2018)* indicate that the number of taxi drivers is unaffected by the market entry of a ride-

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[25] The official Chinese unemployment rate varies between 3,7% (Min) and 4,8% (Max) in the period 1991-2018. It's coefficient of variation ($\frac{\sigma}{\mu}$) is only 5% compared to a global average of 22% among 194 countries (excluding China).

[26] *Feng et al. (2017)* and *Giles, Park, & Zhang (2005)* highlight several peculiarities in the computation of the unemployment rate by Chinese authorities, which affect its explanatory power: (1) The unemployment rate is calculated on the basis of the self-registered unemployed population. Due to the rudimentary developed Chinese welfare system, relevant shares of the population lack the motivation or awareness to register with the labour department. (2) Only people with an urban registration status (Hukou) can register as unemployed, jobless migrants or people from rural areas are not counted. (3) An age limit of 50 and 45 for male and female jobseekers, respectively, ignores the jobless share in the society, who surpasses the age-limit but is not retired yet.

[27] Didi Chuxing's service is classified in the sub-category G-54-541-5413 (Internet-based car service and their drivers) of the transportation, storage and postal industry according to the Chinese industrial classification system (GB/T). The full (Chinese) GB/T-list can be approached via: www.stats.gov.cn/tjsj/tjbz/hyflbz/. Note, that due to peculiarities in the NBS-computations, each value of the period 2012 is displaced by the arithmetic mean of the years 2011 and 2013.

hailing service. However, features of the Chinese market (for instance increases in the number of government licenses) potentially influence $NSP_{i,t}^{TSP}$ via the variance proportion assigned to the share of taxi drivers. To alleviate this concern and to provide control levels against other unobserved variation in the taxi sector, the number of taxicabs per province ($numtaxi_{i,t}$) is included in the model. Furthermore, resident population ($population_{i,t}$) and the share of economically active population ($EAP_{i,t}$) allow to balance time-variant heterogeneity and to mitigate endogenous effects (see subsection 4.6). As in *equation (2)*, a one-period lagged variable of Baidu Index ($Baiduint_{i,t-1}$) is included to observe time-staggered effects. To be more specific, *Equation (3)* typifies the unobserved model for the estimation of *hypothesis 2*:

$$NSP_{i,t}^{TSP} = \beta_1 * Baiduint_{i,t} + \beta_2 * Baiduint_{i,t-1} + \vartheta_1 * numtaxi_{i,t} + \vartheta_2 * population_{i,t} + \vartheta_3 * EAP_{i,t} + \theta_i + \gamma_t + \varepsilon_{i,t} \tag{3}$$

$Baiduint_{i,t}$, $Baiduint_{i,t-1}$, $numtaxis_{i,t}$, and $population_{i,t}$ are log-transformed to provide an interpretation as elasticities.

4.5 Quantifying implications on cross-industry wage levels

An accurate investigation of the intersectoral wage-level effects formulated in *hypothesis 3* requires certain adjustments to the research design proposed in subsection 4.2. While quantifications of *hypothesis 1* and *2* build on aggregated data provided by the NBS, this section utilizes individual social survey data from the CFPS. In contrast to aggregated figures covering all shares of society (e.g. average wage), individual data allows to primarily focus on the relevant proportion of low-income workers. This configuration offers an important advantage: conditional on divergent personal income observations, varying treatment intensities among extrinsically motivated individuals can be reasonably assumed. An emerging job opportunity is irrelevant for individuals, whose current contracted wage exceeds expected incomes from the alternative occupation. In contrast, occupation transition becomes disproportionally attractive for persons who benefit financially. Given the dichotomous variation in the stimulus to switch occupation, this thesis assumes that individuals are treated independently by the exogenous source of variation. In subsection 3.4, average annual gross income levels of full-time Didi-drivers were estimated at 68% of the average mean across industries and occupations. An equivalent of RMB 41.800 (or approximately USD 6.300) in 2016. The further investigation exploits this specific income threshold as a means of treatment identification: high- and low-income workers are defined as individuals with an annual wage above or below this level, respectively. Subsequently, high-income workers can be regarded as control group; low-income individuals as treatment group towards the exogenous event of Didi's market introduction (B. D. Meyer, Viscusi, & Durbin, 1995; Wooldridge, 2015). Measures of income shifts among individuals in intervention and comparison group during the pre- and post-treatment period, i.e. before and after Didi's market intervention, are constructed on CFPS data sets in the periods 2010 and 2016. These periods ideally reflect the evolution of the exogenous influence by Didi: CFPS-observations in 2010 essentially record the base period two years prior to Didi's first presence. In 2016, two years after the turn towards today's major business, the company has been active in >400 cities in China, as confirmed on a request by the author. After mergers with Kuaidi Dache (02/2015) and Uber China (07/2016), Didi served >100 million monthly users in 2016 (Statista, 2017). Both, extensive spatial diffusion and market penetration, suggest a substantial treatment intensity by the exogenous intervention, thereby, exposing effects on personal income.[28] In addition, simplifying the data structure in a two-period configuration mitigates concerns of bias in the statistical inference due to the presence of serial correlation (Bertrand, Duflo, & Mullainathan, 2004). In order to serve the research question formulated in *hypothesis (3)*, individuals are omitted from the sample if they comply with any of the following criteria: (1) unemployed or jobless (e.g. retirement), (2) self-employed or engaged in the family business, (3) engaged in agriculture (4) absence of a strictly positive income in both observed periods. Applying these criteria reduces the original dataset from 36.892 to 2.792 observations with information available in both periods. The fixed/random-effects regression methodology developed in subsection 4.2 is subsequently adjusted to a difference-in-difference (hereafter DID) approach, exploiting a quasi-experimental panel design (Berck & Villas-Boas, 2016). This thesis deploys a triple DID

[28] The CFPS 2016 wave was conducted between 07/2016 and 06/2017.

framework (i.e. difference-in-difference-in-difference) comparing income shifts among (1) low-income and high-income individuals and (2) regions with low and high intensity of Baidu search volume. The comparison to the high-income proportion provides the double difference and the further comparison to provinces with disproportional large Baidu search volume, the triple difference. This approach is specified by *equation (4)*:

$$\delta_4 = \left(\widehat{inc_{2016,li=1}} - \widehat{\mathrm{inc}_{2016,li=0}}\right) - \left(\widehat{inc_{2010,li=1}} - \widehat{\mathrm{inc}_{2010,li=0}}\right) - \left(\left(\widehat{\mathrm{inc}_{2016,BIS=1}} - \widehat{\mathrm{inc}_{2016,BIS=0}}\right) - \left(\widehat{\mathrm{inc}_{2010,BIS=1}} - \widehat{\mathrm{inc}_{2010,BIS=0}}\right)\right) \tag{4}$$

where δ_4 denotes the estimated effect, $\widehat{\mathrm{inc}}$ is a coefficient reflecting the income-implications of an individual's allocation to an independent variable (e.g. low-income worker) before and after the treatment, li is a dummy variable that becomes 1 if an individual's annual gross income in both periods 2010 and 2016 is below the defined threshold ($li(income < RMB\ 41.800\ p.a.) = 1$), and BIS is a binary variable equal to 1, when the person's province of origin is assigned to the largest 30%, with respect to the magnitude of Baidu search volume ($BIS(Baiduint > 500\ p.d.) = 1$). In other words, δ_4 is the deviation over time in the average disparity of income among high- and low-income individuals, further differentiated between provinces with a strong or weak activity of Didi as approximated by Baidu search volume. Another reason for the modification of the econometric approach in this subsection derives from the quality of a DID-design to circumvent many of the endogenous effects that arise in data setups with heterogeneous individuals (Berck & Villas-Boas, 2016). Concerns due to static heterogeneity as well as unobserved variables are alleviated given the parallel trends assumption between control- and treatment observations (Bruce D. Meyer, 1995). *Equation (4)* can be transferred to a regression design that returns standard errors of coefficients. This setup allows the asymptotical validation of estimates using statistical inference. The triple DID model to examine *hypothesis 3* is described by *equation (5)*:

$$\ln(Income) = \alpha + \delta_0 * y2016 + \beta_1 * li + \beta_2 * BIS + \delta_1 * y2016 * li + \delta_2 * li * BIS + \delta_3 * y2016 * BIS + \delta_4 * y2016 * li * BIS + \vartheta_s * \mathbf{X}_{i,t} + \varepsilon_{i,t} \tag{5}$$

Within this equation, income is log-transformed since percentage alterations are of primary interest. α denotes the intercept, $y2016$ is a binary variable equal to 1 in the post-treatment period (2016), δ_0 reflects overall income developments throughout 2010 and 2016. Coefficient β_1 investigates the effects of li prior to the exogenous variation. β_2 controls existing unobserved heterogeneity prior to the market entry of Didi in provinces where BIS equals 1. δ_1 evaluates whether the treatment group li is disproportionally affected by the exogenous variation, which is expected to be positive according to *hypothesis 3* (first DID). Moreover, estimates between provinces with strong or weak market presence are contrasted (second DID), to strengthen the causal conclusion that the hypothesized effect is attributable to Didi's activity. δ_2 estimates income disparities between treatment and comparison group in BIS provinces prior to Didi's entry. δ_3 controls overall income deviations in BIS-provinces between 2010 and 2016 irrespective of li. δ_4 estimates the indicator of interest, as previously described in *equation (4)*. Coefficient ϑ_s denotes the effect of control variable s from set $\mathbf{X}_{i,t}$, including factors that have proven to affect income inequality in China, e.g. Hukou status (Qiu & Zhao, 2019), age and age^2 (Zhong, 2011), years of education (Narayan & Smyth, 2006), and gender (Tang & Scott, 2017). Control variables foster the validity of the parallel trends assumption by reducing the variance within the error term ε (Wooldridge, 2015).

4.6 Endogeneity examination

Given the non-experimental composition of the explored data sources in *hypothesis 1* and *2*, unobserved effects may impact the accuracy of coefficients when estimating the hypothesized relationships. Although the main empirical approach in this thesis is likely to exclude a variety of omitted factors (e.g. fixed-effects), estimate validity could be threatened if endogenous relations among the variables are not investigated and thoroughly purged out (Antonakis, Bendahan, Jacquart, & Lalive, 2014). An endogenous bias can stem from a plethora of origins and is characterized by a correlation between the coefficient β and the model's error term ε. Considering research design and data structure, endogeneity caused by omitted variables bias (OVB) will subsequently be analyzed.[29] OVB becomes relevant, when an unobserved variable $z_{i,t}$[30] is neglected in the model even though it systematically affects both explanatory and response variable. As displayed in illustration 11, time-varying socio-demographic or economic factors among the provinces may simultaneously encourage the independent variable Baidu Index and the dependent variable of interest (e.g. population may influence both employment and Baidu Index). In addition, time variation in Didi's staggered expansion potentially influences the magnitude of Baidu Index if the permanence of Didi's market activity is assumed to influence users and drivers (e.g. as a result of enhanced familiarity with the service or advertisement intensity). An endogenous bias might be induced, when Didi's strategical decision to enter a province is not conditional on provincial characteristics that simultaneously affect the dependent variable (Berger, Frey, et al., 2018; Guo et al., 2018). From a prospective view, an intuitive response to prevent for endogeneity bias is to identify and incorporate relevant (observable) variables $\boldsymbol{Z}_{i,t}$ in the model (Antonakis et al., 2014). For this purpose, a two-staged approach, considering impacts of provincial qualities on both market entry and Baidu Index is applied. A first stage test examines whether the perpetuity of Didi's presence in a certain province influences Baidu Index. In case of significance, a second stage regression exposes which, if any, observable socio-demographic qualities build a strategic pattern for Didi's decision to target a market. Table 2 illustrates the results of regressing Didi's attendance in a certain province in months on the respective magnitude of Baidu Index, using a cross-sectional design with data of 2017. The small but significant coefficient ($p<0,01$) becomes insignificant as soon as control variables are added to the model, indicating a missing relation between the durability of Didi's attendance and Baidu index. Consequently, further investigations

[29] Building on *Antonakis et al. (2014)* several causes of endogeneity bias have been considered (e.g. common variance methods, measurement errors, simultaneity, omitting selection, omitted fixed effects and consistency of inference). Other situations are excluded from the examination since they are rather controlled in the model or irrelevant for the proposed research design.

[30] Or multiple variables denoted by $\boldsymbol{Z}_{i,t}$.

on endogenous effects from the permanence of activity are dispensable. To examine the alternative origin of endogeneity bias, a multivariate longitudinal regression is applied, as presented in table 3, identifying provincial characteristics that influence both Baidu index and the accordant dependent variable. Provincial variables cover characteristics with regard to education, economic status, social dependency, internet prevalence and travel demand. When regressed with each of the dependent variables ($NSP_{i,t}^{TSP}$ and $CPI_{i,t}^{T}$) as well as the explanatory variable Baidu Index ($Baiduint_{i,t}$), joint relations are revealed, as highlighted by

Directions of endogenous confounding factors

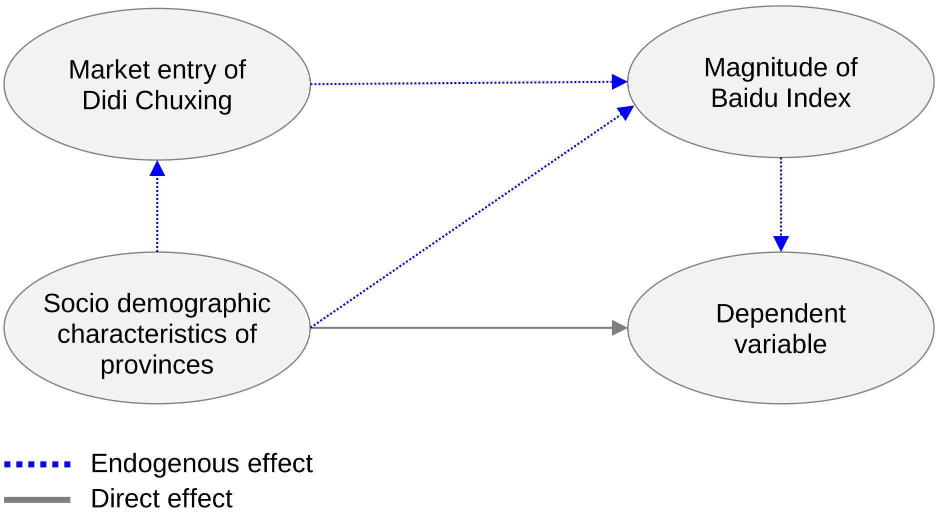

Illustration 11: Directions of endogenous confounding factors (own illustration)

Effects of Didi's staggered market diffusion on Baidu Index
31 provinces, (2017)

	Outcome: Baidu Index (ln)	
	(1)	(2)
Intercept	**1,59***** (0,70)	**-9,45***** (2,65)
Duration of Didi's activity (in months)	**0,08***** (0,01)	**-0,001** (0,01)
Full set of control variables	**NO[1)]**	**YES[1)]**
Year of observation	2017	2017
Observations	31	31
Adjusted R^2	0,43	0,85
P-value model	*p < 0,001*	*p < 0,001*
Variance inflation factor (max.)	-	4,96

Notes: [1)] The set of control variables include resident population (ln), number of university students per 100.000 inhabitants (ln), per-capita gross regional product (ln), number of mobile internet subscribers (ln), and urbanization ratio (% of population). Baidu Index represents the log-transformed daily average search volume with the keyword "Didi Chuxing/Dache". Robust standard errors are in parentheses. Statistical significance is denoted by: *p < 0,01*** p < 0,05** p < 0,1**.

Table 2: Effects of Didi's staggered market diffusion on Baidu Index

blue frames. As suggested by the findings, resident population, economically active population and internet penetration are integrated into the computations of *equation (2)* and *(3)*, respectively, to suspend endogenous variance. Note, that the examination of *hypothesis 3* controls endogeneity within the DID approach. In addition, Baidu Index in a continuous form is not included in the model.

Multivariate effects of time-varying provincial characteristics on Baidu Index and response variables

31 provinces, (2008-2017)

Independent variable (provincial characteristics):	Dependent variable (Outcome):		
	NSE^{TSP} (ln)	CPI^{T} (%)	Baiduint (ln)
Intercept	**0,78** (2,01)	**-** -	**-** -
Resident population (ln)	**0,88***** (0,12)	**-4,68** (13,75)	**8,15***** (3,41)
University students per 100.000 inhabitants (ln)	**0,13** (0,21)	**-0,75** (4,34)	**1,10** (1,20)
Per-capita gross regional product (ln)	**0,31** (0,19)	**11,92***** (3,09)	**1,01** (0,90)
Economically active population (% of total)[1)]	**-1,28** (1,15)	**59,08***** (13,82)	**-53,92***** (6,42)
Urbanization ratio (%)	**-0,00** (0,00)	**-0,00** (0,00)	**-0,00** (0,00)
Internet penetration (% of population)	**0,40** (0,53)	**-12,00***** (7,02)	**12,48***** (2,41)
Passenger traffic (ln)	**-0,01** (0,04)	**0,45** (0,93)	**-1,42***** (0,26)
Years of observation	2008-2017	2008-2017	2008-2017
Observations	310	310	310
Groups	31	31	31
Adjusted R^2	0,38	0,49	0,78
P-value model	*p < 0,001*	p < 0,001	*p < 0,001*
Heteroscedasticity (Breusch-Pagan)	*YES*	*YES*	*YES*
Serial correlation (Breusch-Godfrey/Wooldridge)	*NO*	*YES*	YES
Model (Hausman)	*Random*	*Fixed-effects*	*Fixed-effects*

Notes: [1)] The economically active population is computed using survey data provided by NBS. Model-type is deployed according to the presence of observed correlation between explanatory variables and entity heterogeneity as indicated by the Hausman-test. The occurrence of heteroscedasticity and serial correlation is tested using the Breusch-Pagan and Breusch-Godfrey/Wooldridge test, respectively. In case of occurrence, robust covariance estimation (sandwich estimator) are applied to correct the distortions. Baidu Index represents the log-transformed daily average search volume with the keyword “Didi Chuxing/Dache”. Robust standard errors are in parentheses. Statistical significance is denoted by: *p < 0,01*** p < 0,05** p < 0,1**.

Table 3: Multivariate effects of time-varying provincial characteristics on Baidu Index and response variables

4.7 Descriptive results

4.7.1 NBS data (*hypothesis 1* and *2*)

Table 4 provides an overview of descriptive statistics quantifying between-variance among provinces in the NBS sample, covering explanatory, control and response variables incorporated in *equation (2*) and *(3)*. In the interest of brevity, the description is limited to the contrast between 2008 and 2017. A full register of periods omitted in this subsection is provided in Appendix VI. Across all provinces, employment and price indices increased significantly throughout the period of observation. In contrast, active population, resident population and number of taxicabs in operation remain widely constant. The sharp decline in passenger traffic is mainly driven by decreasing highway traffic, while aviation and railway travel constantly expand. Moreover, the volume decrease is offset by increasing average passenger kilometres indicating longer distances per trip (NBS, 2019). Illustration 12 presents the evolution of Baidu Index volume among the 31 provinces, reflecting significantly variation of the activity intensity of Didi Chuxing.

4.7.2 CFPS data (*hypothesis 3*)

Illustration 14 highlights time-invariant characteristics of the 2.792 observations within the CFPS sample. The figures indicate a well-balanced distribution regarding Hukou status, gender and treatment assignment. In addition, a summary of time-variant variables included in the evaluation of *hypothesis 3* is displayed in table 5. The figures highlight a perceptible increase in average income, which almost doubles in size throughout the period of observation. However, the relatively large SD indicates a substantial income inequality with only a marginally appease in 2016. Conditional on the expected shift of 6 years resulting from the longitudinal setup of data, age-distribution remains constant. A very similar absence of dynamic is suggested by the invariant distribution of education. Variation in standardized income shifts between low- and high-income individuals (i.e. treatment and comparison group) in pre- and post-treatment period is displayed in illustration 13.

Growth of Baidu search intensity on province level

31 provinces, (2008-2017)

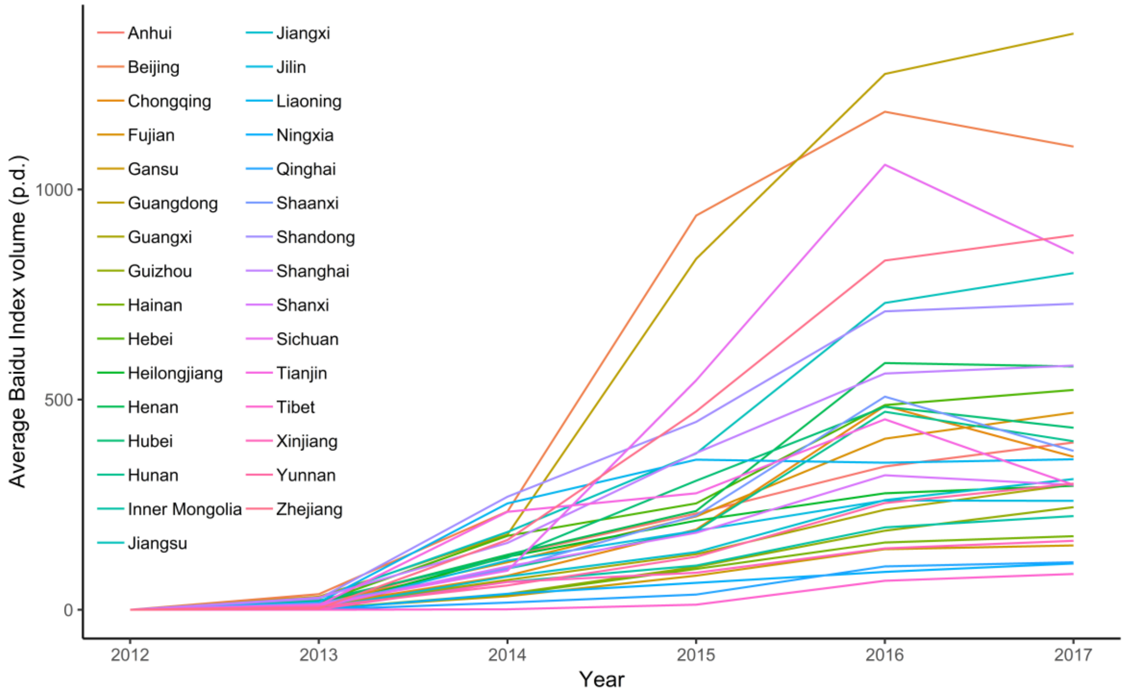

Illustration 12: Growth of Baidu search intensity on province level (own illustration)

A summary of time-variant descriptive statistics (NBS data)

31 provinces, (2008 vs. 2017)

Variable:	Mean (2008)	SD (2008)	Min. (2008)	Max. (2008)	Mean (2017)	SD (2017)	Min. (2017)	Max. (2017)
Consumer price index (transport)	100	0	100	100	105,5	5,5	95,5	116,1
Self-employment in transport, storage and post	95.458	80.642	6.400	401.000	165.200	138.619	10.700	630.700
Baidu Index (average p.d.)	0	0	0	0	437	298	85	1371
Consumer price index (fuel)	100	0	100	100	107,1	4,0	98,7	118,2
Passenger traffic (million)	918,9	925,3	68,6	4.752	578,5	382,6	13,2	1374,2
Consumer price index (public transport)	100	0	100	100	116	16,1	84,9	189,8
Economically active population (% of total)	73	3	66	80	72	3	68	78
Number of taxi cabs	31.252	19,843	1.341	80.376	35.574	19.886	2.218	82.067
Population (million)	42,4	26,8	2,9	98,9	44,8	28,2	3,4	111,7

Notes: Number of observations = 62.

Table 4: A summary of time-variant descriptive statistics (NBS data)

Income developments between treatment and control group (CFPS data)

(2010 vs. 2016)

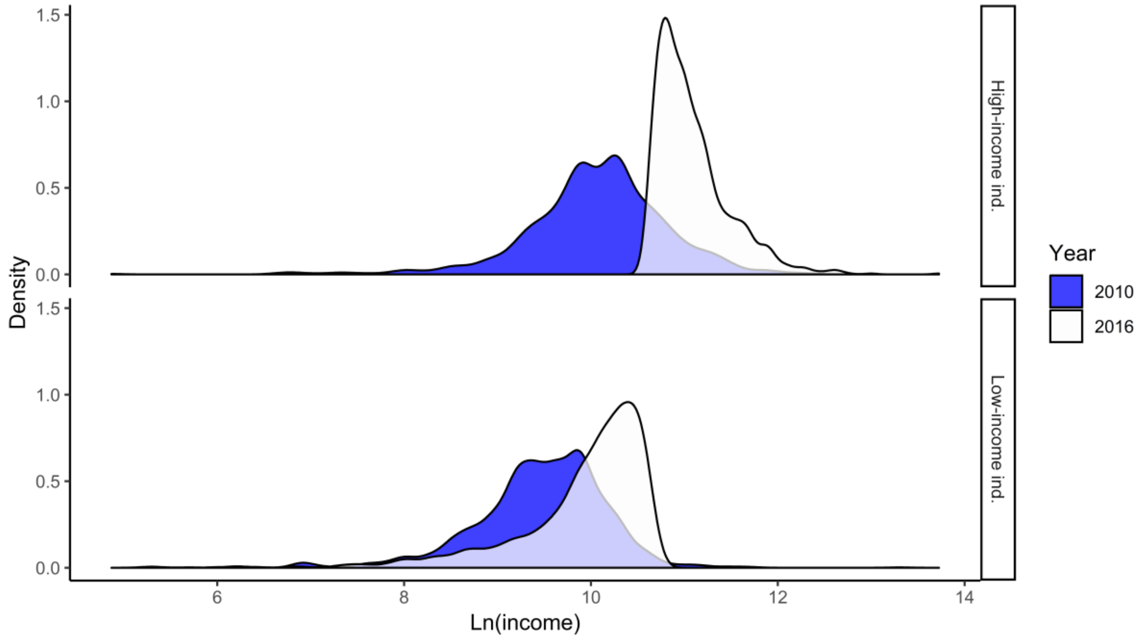

Illustration 13: Income developments between treatment and control group (own illustration)

Time-invariant characteristics (CFPS data)

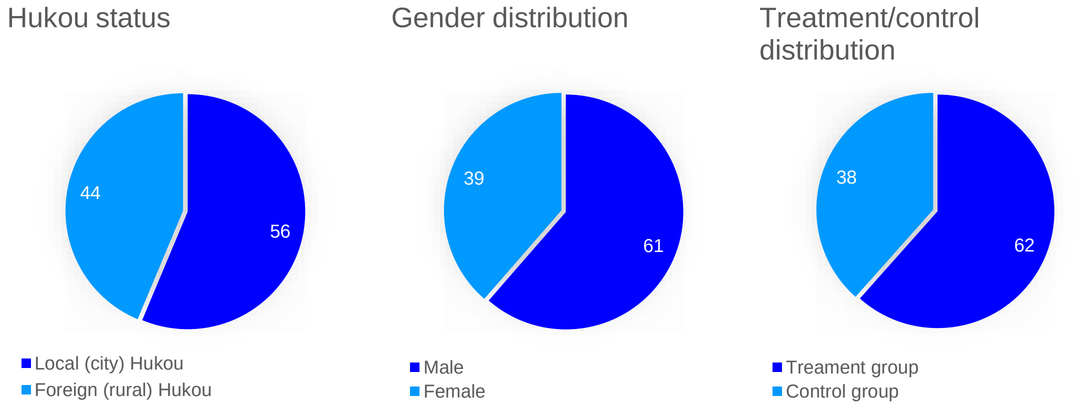

Illustration 14: Time-invariant descriptive statistics (CFPS data) (own illustration)

A summary of time-variant descriptive statistics (CFPS data)

(2010 vs. 2016)

Variable:	Mean (2010)	SD (2010)	Min. (2010)	Max. (2010)	Mean (2016)	SD (2016)	Min. (2016)	Max. (2016)
Income (RMB)	21.306	21.189	130	600.000	41.571	37.092	400	913.475
Ln(income)	9,7	0,8	4,9	13,3	10,3	0,8	6,0	13,7
Age (years)	37,1	9,7	16,0	70,0	43,2	9,7	22,0	76,0
Education (years)	10,9	3,8	0,0	22,0	10,9	3,9	0,0	22,0

Note: Number of observations = 2.792.

Table 5: A summary of time-variant descriptive statistics (CFPS data)

5 Results

5.1 Didi's effect on mobility price levels

Table 6 presents estimates of *equation (2)* documenting that Didi's presence intensity is associated with a relative decrease in average mobility price levels. Prior to the estimation, several tests are applied to consider parametric assumptions. First, an F-test between simple OLS and fixed-effects regression evaluates whether the sum of static heterogeneity is equal to zero. The null-hypothesis is significantly rejected (p<0,01) which confirms the validity of the approach proposed in subsection 4.2. Second, the presence of correlation among explanatory variables and idiosyncratic error term ε is investigated by the Hausman-test. Again, the null hypothesis is significantly rejected (p<0,01); consequently, a fixed-effects model is applied to control for area-static heterogeneity. The null hypothesis in both Breusch-Godfrey/Wooldridge and Breusch-Pagan test is significantly rejected (p<0,01), pointing to the presence of heteroscedasticity and serial correlation. To provide profound estimations of asymptotical inference, a robust covariance matrix (sandwich estimator) is applied. Column (1) of table 6 reports the baseline model with a fixed-effects regression of Baidu Index and its one-period-lagged equivalent on consumer price indices of the category transportation. In a first step to eliminate alternative variation, a set of time-varying control variables is incorporated in column (2). The analysis of unobserved shocks within the period of observation reveals a joint significance of time fixed-effects (p<0,01). To account for these trends, time fixed-effects are integrated in a second step as presented in column (3). After incorporating area and time fixed-effects, both estimated coefficients of Baidu Index (immediate and distributed lag) appear statistically significant (p<0,01), indicating an immediate and deferred effect on consumer mobility price levels by the activity of Didi. The results suggest a negative disproportional relation: a 1% increase of Baidu Index causes a marginal 0,012 p.p. decline of consumer mobility prices o.a.c.p.[31] Considering the elasticity's infinitesimal magnitude, the relevance of the effect may become more obvious

[31] An overview of coefficient interpretation in log-transformed regression models is provided by e.g. *Wooldridge (2015)* or *Benoit (2011)*.

when the overall development of Baidu Index is incorporated in the interpretation. From its first occurrence in 2012 untill the end of 2017, Baidu Index shows a rapid (temporarily exponential) growth by the factor 38,06 o.a. (see also illustration 12). Converted to the estimated regression, the model predicts an average decline of consumer mobility prices by -4,47 p.p. across provinces in the respective period. The contrast to the index' overall SD of 1,98 p.p., between 2012 and 2017, exemplifies the considerable dimension of the estimated effect. Moreover, only a limited proportion of 0 to 15% in daily mobility is allocated to ride-hailing services between 2012 and 2017. Although e-hailing services account only for a limited weight in the variety of personal transport options covered by the consumer price index, the emerging dynamic markedly affect its development. The growing importance of e-hailing in daily mobility is likely to further accentuate the effect in future research. The given arguments substantiate the influence in a relevant magnitude of ride-hailing services on individual mobility prices.

Didi's effect on mobility price levels

31 provinces, (2008-2017)

	Outcome: CPI^T (2008=100)		
	(1)	(2)	(3)
Baidu Index (ln)	**1,15***** (0,11)	**-0,14** (0,09)	**-0,72***** (0,18)
Baidu $Index_{t-1}$ (ln)	**-0,91***** (0,09)	**-0,59***** (0,12)	**-0,49***** (0,15)
Internet penetration (% of total)		**24,67***** (3,73)	**12,49** (12,91)
Economically active population (% of total)[1)]		**15,89** (20,14)	**20,42** (19,26)
CPI fuel (2008=100)		**0,05***** (0,01)	**0,11** (0,07)
CPI public transportation (2008=100)		**0,11***** (0,01)	**0,11***** (0,01)
Time fixed-effects			**YES**
Years of observation	2008-2017	2008-2017	2008-2017
Observations	310	310	310
Groups	31	31	31
Adjusted R^2	0,07	0,58	0,68
P-value model	*p < 0,001*	p < 0,001	*p < 0,001*
Heteroscedasticity (Breusch-Pagan)	*YES*	*YES*	*YES*
Serial correlation (Breusch-Godfrey/Wooldridge)	*YES*	*YES*	YES
Time fixed-effects (F-test)	-	-	*YES*

Notes: [1)] The economically active population is computed using survey data provided by NBS. Robust standard errors are in parentheses. Statistical significance is denoted by: *p < 0,01*** p < 0,05** p < 0,1**.

Table 6: Didi's effect on mobility price levels

5.2 Didi's impact on independent employment

In advance of the estimation of *equation (3),* an equal spectrum of tests, as introduced in subsection 5.1, is applied with several diverging outcomes. First, an absence of correlation between static heterogeneity and explanatory variables is indicated by the Hausman-test (p>0,1). Therefore, a random-effects model is favourable and subsequently applied. Random-effects regressions control for autocorrelation within the static heterogeneity term θ_i. However, Breusch-Pagan and Breusch-Godfrey/Wooldridge indicate heteroscedasticity as well as serial correlation in the idiosyncratic error ε (p<0,01). Similar to subsection 5.1 a robust covariance matrix estimator is applied to alleviate bias in the computation of statistical inference. The results are presented in table 7, suggesting a time-staggered positive correlation between the activity of Didi and the number of urban self-employed individuals in transport, storage and post. Column (1) displays the baseline random-effects estimation, restricted to response and explanatory variables. In column (2), additional control variables are incorporated into the model.

Didi's impact on self-employment

31 provinces, (2008-2017)

	Outcome: NSE^{TSP} (ln)	
	(1)	(2)
Intercept	**11,19***** (0,17)	**1,25** (1,53)
Baidu Index (ln)	**0,03***** (0,01)	**0,01** (0,01)
Baidu Index$_{t-1}$ (ln)	**0,03***** (0,01)	**0,04***** (0,01)
Number of taxicabs (ln)		**0,34*** (0,18)
Resident population (ln)		**0,64***** (0,15)
Economically active population (% of total)[1)]		**1,62** (2,11)
Years of observation	2008-2017	2008-2017
Observations	310	310
Groups	31	31
Adjusted R^2	0,23	0,38
P-value model	*p < 0,001*	p < 0,001
Heteroscedasticity (Breusch-Pagan)	*YES*	*YES*
Serial correlation (Breusch-Godfrey/Wooldridge)	*YES*	*YES*
Time fixed-effects (F-test)	-	*NO*

Notes: [1)] The economically active population is computed using survey data provided by NBS. Robust standard errors are in parentheses. Statistical significance is denoted by: *p < 0,01*** p < 0,05** p < 0,1**.

Table 7: Didi's impact on self-employment

In contrast to subsection 5.1, the F-test for joint significance of time fixed-effects reveals no relevant factors (p>0,1) and thus omitted in the computation of *equation (3)*. In addition, the immediate effect of Baidu Index on the response variable is not statistically significant. Under this circumstance, the estimated relation in column (2) indicates a temporarily delayed disproportional positive elasticity: a 1% increase of Baidu Index causes a marginal 0,04% increase of self-employment in transport, storage and post in the subsequent period o.a.c.p. In a similar approach as applied in subsection 5.1, fitted value estimates of the model are utilized to provide predicted outcomes of Baidu Index shifts between 2012 and 2017. Across provinces, this examination indicates an average growth of 18,84% in self-employment due to the activity of Didi in the respective period. Predicted results, however, are likely to be well below the true magnitude of the employment effect, considering the significant proportion of part-time drivers who do not register themselves as self-employed with the government authorities. Hence, the actual extent of the phenomenon may not be accurately reflected in official statistics of self-employment, which constitute informed political decisions. Implication for stakeholder of this result are reconsidered in the discussion of section 6.

5.3 Didi's impact on cross-industry wage levels

Table 8 reports the results of *equation (5),* with baseline double DID-coefficients provided in column (1). The figures illustrate an average income increase of 95-96% between 2010 and 2016. Yet, beneath these overall advances, the magnitude of inequality between low- and high-income proportions increased by 47-50%, revealing a disproportionally smaller salary growth of low-income individuals. All obtained results are statistically significant (p<0,01). Coefficients of the model incorporating a full set of control variables are presented in column (2). The variables of interest remain largely equal in magnitude and significance; additional coefficients, however, allow to study the distribution of income in more detail. Figures point to a systematic income disparity of 19-20% between male and female persons as well as 8-10% between local and migrant workers, respectively. The attainment of education depicts a linear positive relation to expected earnings: an additional year of education increases income by 3% o.a.c.p. Eventually, age shows a convex non-linear relationship to income with a reversal point at the age of 40. Again, all documented figures are highly statistically significant (p<0,01). The triple DID-estimation results displayed in column (3), are obtained by the integration of BIS, which dichotomously assorts provinces with respect to the observed Baidu Index search volume (see subsection 4.5). To examine the formulated research question, control variables are again incorporated and estimates of the full model are presented in column (4). In advance of Didi's market introduction, average income and income inequality in provinces with a high Baidu search volume ($BIS = 1$) surpass the accordant figures in provinces with moderate volume ($BIS = 0$) by 20-26% and 11-12%, respectively. This pro-

Average cross-industry income effects of Didi's introduction

2.792 observations, (2008 vs. 2016)

	Outcome: Ln(income)			
	(1)	(2)	(3)	(4)
Intercept	**10,09***** (0,02)	**7,73***** (0,11)	**9,97***** (0,03)	**7,53***** (0,11)
$y2016$ (2016=1)	**0,95***** (0,02)	**0,89***** (0,02)	**1,01***** (0,04)	**0,96***** (0,04)
li ((income<RMB 41.800)=1)	**-0,66***** (0,02)	**-0,55***** (0,02)	**-0,59***** (0,03)	**-0,46***** (0,03)
$y2016 * li$	**-0,47***** (0,03)	**-0,43***** (0,03)	**-0,52***** (0,05)	**-0,50***** (0,05)
Age		**0,08***** (0,005)		**0,08***** (0,005)
Age^2		**-0,0009***** (0,00006)		**-0,001***** (0,00006)
Years of education		**0,03***** (0,002)		**0,03***** (0,002)
Gender (male=1)		**0,19***** (0,01)		**0,20***** (0,01)
Hukou (local=1)		**0,08***** (0,01)		**0,10***** (0,01)
BIS ((Baidu Index>500 p.d.)=1)			**0,20***** (0,04)	**0,26***** (0,03)
$li * BIS$			**-0,11**** (0,05)	**-0,12***** (0,04)
$y2016 * BIS$			**-0,10*** (0,05)	**-0,10**** (0,05)
$y2016 * BIS * li$			**0,09** (0,07)	**0,12*** (0,06)
Years of observation	2010/2016	2010/2016	2010/2016	2010/2016
Observations	2.792	2.792	2.792	2.792
P-value model	*p < 0,001*	*p < 0,001*	*p < 0,001*	*p < 0,001*
Adjusted R^2	0,41	0,48	0,42	0,49

Notes: Robust standard errors are in parentheses. Statistical significance is denoted by: *p < 0,01**** *p < 0,05*** *p < 0,1**.

Table 8: Average cross-industry income effects of Didi's introduction

vides statistically significant evidence (p<0,01) for an exceptionally successful expansion of Didi's business model in affluent urban areas with a distinct income inequality. The advance of income growth, however, appears to be 10% smaller in provinces with a particularly high Baidu search volume, compared to the overall average development in the period of observation (p<0,01). A very interesting im-

Average cross-industry income after Didi's introduction

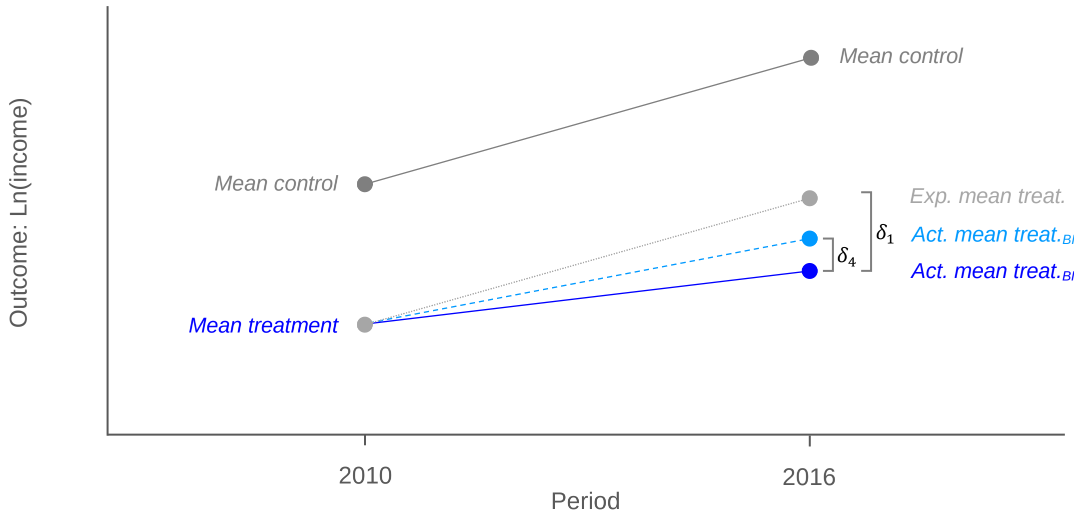

Illustration 15: Average cross-industry income after Didi's introduction (own illustration)

Income deviations between BSI-groups after Didi's introduction

2.792 observations, (2010 vs. 2016)

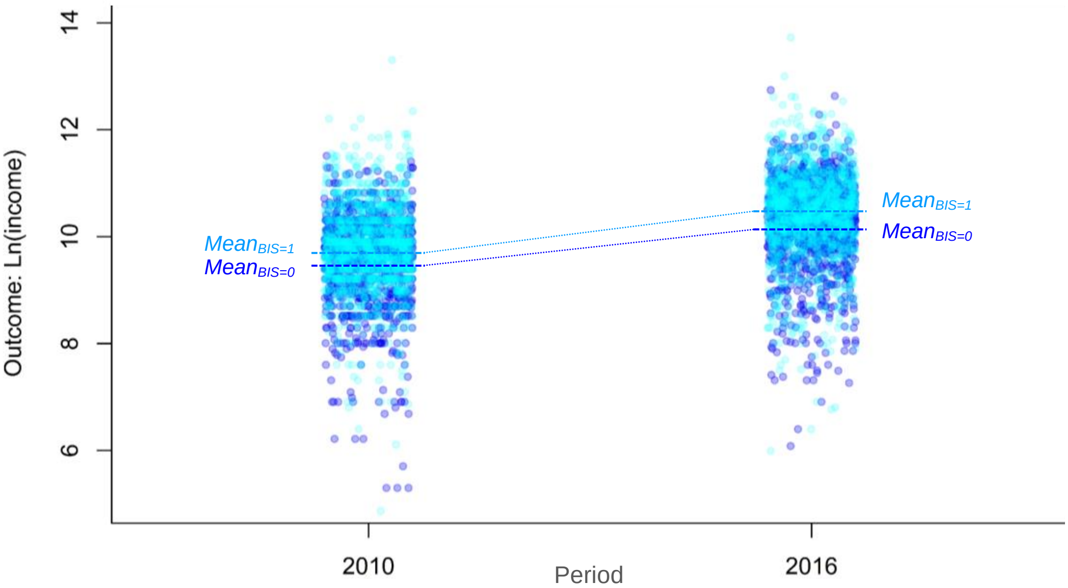

Illustration 16: Income deviations between BSI-groups after Didi's introduction (own illustration)

plication is exposed by the isolated wage-effect of low-income individuals, differentiated between provinces with conspicuously high or moderate Baidu search volume: average income gains in the first-mentioned provinces surpass the development of the respective fraction in the last-mentioned provinces by 12% o.a. This statistically significant result ($p<0,1$) particularly refers to the formulated research hypothesis. Findings can be interpreted as follows: in contrast to the argumentation of *hypothesis 3*, earning advances of low-income individuals are disproportionally smaller compared to high-income-individuals. However, the income-differential to high-income workers is about 12% smaller for individuals in regions with a disproportional large Baidu-search volume. This effect indicates, that the activity of Didi alleviates income inequality as argued in *hypothesis 3*. The relationship between divergent income developments among the observed groups is visualized in illustration 15. In addition, illustration 16 displays the actual mean-income shift contrasted between provinces with strong and weak Baidu search intensity.

5.4 Sensitivity examination

5.4.1 Evaluation of pre-existing trends

A general concern about the validity of estimations, utilizing a limited period of observations, is that effects may reflect the dynamics of unobserved pre-existing trends rather than the hypothesized causal relation. To assess whether such differential trends exist in the evaluation of *hypothesis 1* and *2*, illustration 17 visualizes the dynamic of the response variables before and after the market entry of Didi. Both, the number of self-employed individuals in transport, storage and post ($NSP_{i,t}^{TSP}$) and the consumer price index in the category transportation ($CPI_{i,t}^{T}$) is transformed to an index with the base year 2008 (2008=100). Moreover, the market entry of Didi Chuxing in 2012 is incorporated (vertical blue line). The variation within the number of self-employed individuals increases significantly, while consumer prices show a perceptible antidromic trend after the market entry of Didi between 2012 and 2014. This finding largely alleviates concerns that the estimated impact of Didi's activity on the accordant response variables is actually driven by unobserved pre-existing trends.

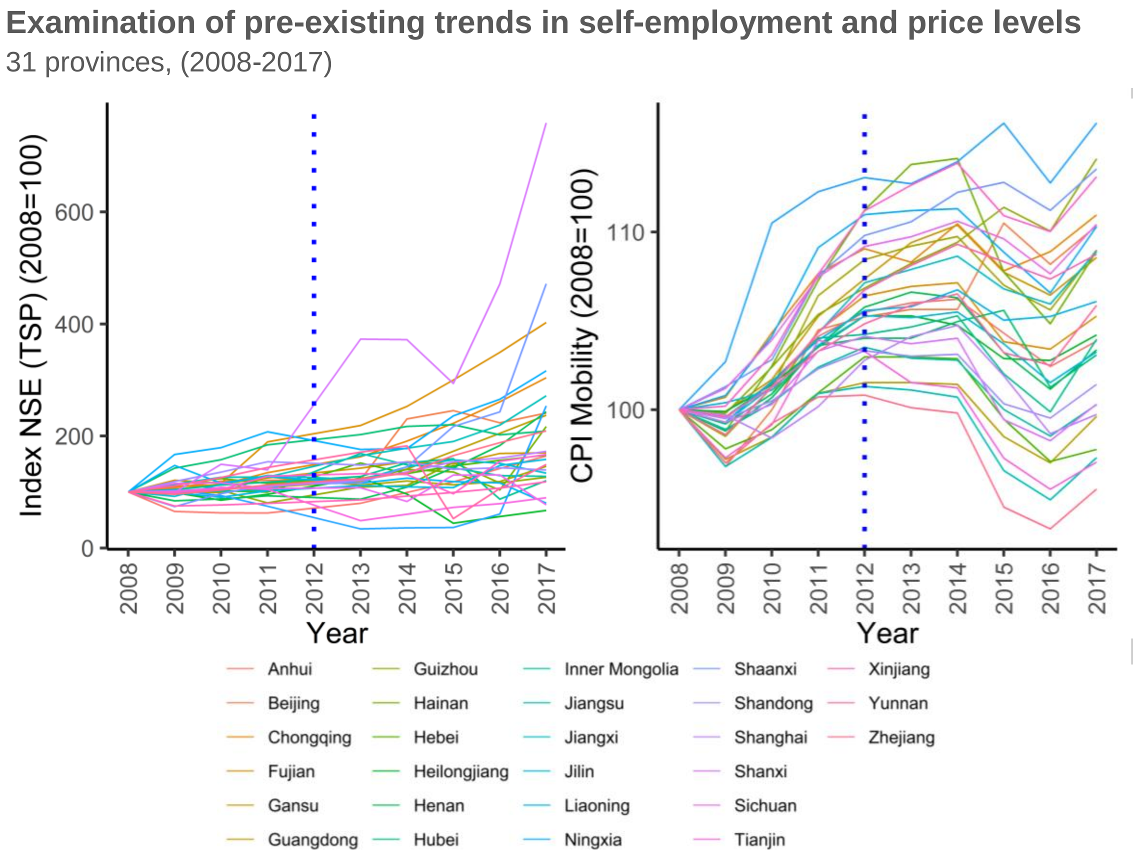

Illustration 17: Examination of pre-existing trends in self-employment and price levels (own illustration)

5.4.2 Sensitivity examination of DID treatment identification

As a means of additionally substantiating the validity of treatment identification applied in DID-models, this subsection provides evidence from a placebo test. The test specification randomizes the assigned treatment distribution with respect to personal income (li) and Baidu Index search intensity (BIS), to exemplify that the obtained estimates are clear outliers relative to the random distribution of placebo values. Placebo distributions are generated by randomly assigning individuals from the observed sample to either treatment or comparison group with regards to personal income (li) and Baidu Index search intensity (BIS). To construct a viable amount of test distributions, 100 random assignments are generated. Each of the obtained alternative distributions is then utilized to estimate a full specification of *equation (5)*. The estimated effects of the parameters of interest (δ_1 and δ_4) on log-transformed income are displayed in Illustration 18. In addition, coefficients from table 8, representing estimates with the actual treatment identification, are incorporated in the illustration (vertical blue line). In both cases, the disparity of actual and placebo values is significant: At most 2% of random placebo estimates surpass the corresponding genuine coefficient. Hence, the test validates the applied treatment identification and corroborates the interpretation that the activity of Didi within a certain province significantly affects wage advances of low-income individuals.

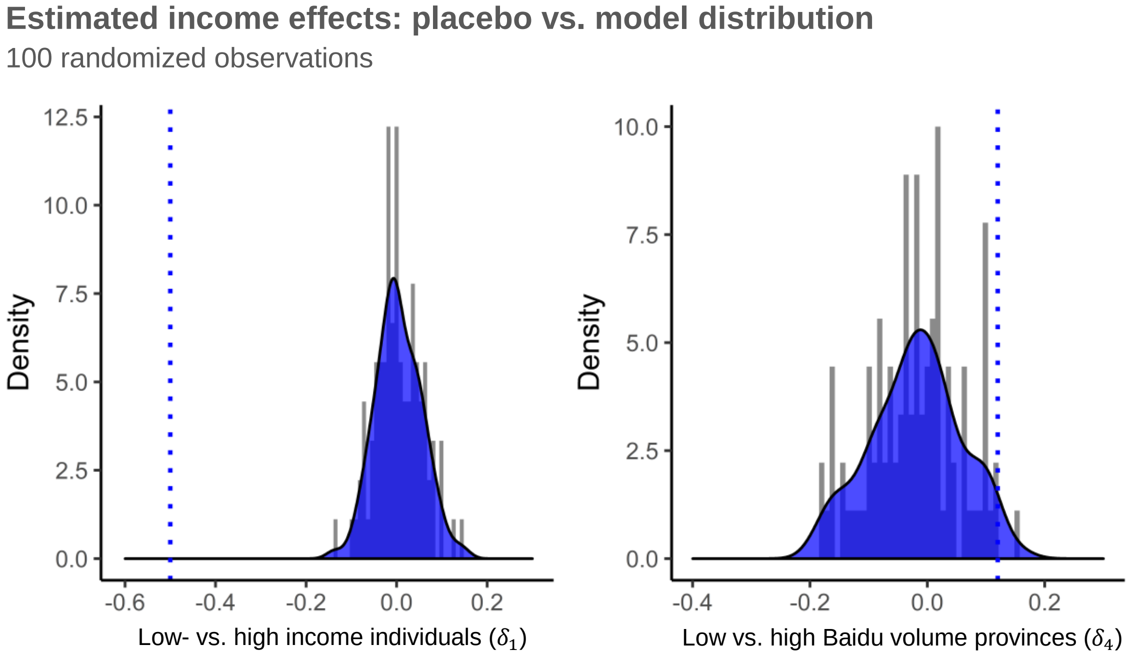

Illustration 18: Estimated income effects: placebo vs. model distribution (own illustration)

6 Discussion and implications: prospects and limitations

6.1 Implications and conclusion

6.1.1 Discussion of *hypothesis 1*

A linear negative correlation between consumer mobility prices and market adoption of e-hailing services was formulated in *hypothesis 1* and confirmed statistically by the empirical analysis in section 5.1. In juxtaposition to previous studies, focusing on other geographical areas or divergent subsections of the SE, the obtained findings of this thesis are confirmed in terms of declining consumer prices (Fradkin et al., 2017) and increasing consumer surplus (P. Cohen, Hahn, Hall, Levitt, & Metcalfe, 2016; Fraiberger & Sundararajan, 2015; Kiesling, Munger, & Theisen, 2018; Lam & Liu, 2017). This coherence of diverse literature streams corroborates the causal interpretation that intrinsic qualities of SE-platforms (e.g. productivity advances and disintermediation) typically entail declining consumer prices. Several economic effects are suggested by this inference: first, digital rental platforms increase the allocative efficiency by creating economies from the direct supplier-to-consumer exchange (Fraiberger & Sundararajan, 2015). Second, the mobilization of omnipresent excess capacities creates an alternative source of supply with perceptible competitive effects on incumbent providers (Berger, Chen, et al., 2018; Fradkin et al., 2017). Third, temporary allocation generates additional benefits for consumers who previously could not afford ownership, thereby, causing a consumption upgrade towards higher-value goods and services. Considering the rapid average income development in China (see also subsection 5.3), this effect is additionally intensified by changing consumer behaviour (Ling, 2012). On the one hand, this upgrade might induce altering travel preferences. Individuals could substitute the less convenient, but cheaper, public transit with individual mobility offers as soon as they become affordable. Thereby, advances in urban sustainability (e.g. air pollution) and accessibility (e.g. congestion) are at least partially obliterated despite substantial capacity increments of e-hailing technologies (Jin et al., 2018; Z. Li et al., 2017; X. Wu & Zhi, 2016). On the other hand, rental marketplaces reduce incentives for long-term investments in fixed assets (e.g. vehicles), since rental options offer an inexpensive, but flexible and similarly convenient consumer experience (Fraiberger & Sundararajan, 2015; Möhlmann, 2015).

6.1.2 Discussion of *hypothesis 2*

The quantification of *hypothesis 2* reveals a deferred increase of self-employment relative to population and proportion of economically active residents due to the expanding activity of Didi. Again, findings of this analysis confirm the results of related empirical work investigating impacts in other geographical areas or subsections of the SE (B. Fang et al., 2016; Z. Li et al., 2018). Moreover, it contributes to several qualitative discussions on altering working conditions through the rapid adoption of peer-to-peer SE-marketplaces (Ganapati & Reddick, 2018; Peticca-Harris, DeGama, & Ravishankar, 2018; Schor, 2017; Sundararajan, 2018; Vallas, 2018). Two competing narratives about the future of work, developed by the referred scholars, relate to the obtained results:

(1) the narrative of the "empowered microentrepreneur" emphasizes sharing platforms as flexible providers of a seamless work opportunity to numerous stakeholders. A platform-mediated work organization can provide a valuable source of income for individuals. It can particularly attract retirees with insufficient pensions, middle-aged workers facing difficulties to find a job after being dismissed, students coping with institutional fees, stay-at-home parents and individuals during times of job transition. In addition, SE-companies turn out to absorb large proportions of decruited labour supply from capacity shifts in traditional industries (e.g. the coal and steel industry in China) (Didi Chuxing, 2017; Fraiberger & Sundararajan, 2015). This perspective is corroborated by several findings in this thesis. Comparably liberal regulative requirements and the mobilization of excess capacity substantiate low entry costs for providers (see section 2). Part-time drivers, for instance, face slightly higher marginal costs but no fixed investment are required for the supply. Hence, ride-hailing has become an economically viable part-time occupation for every second driver on the Didi platform. Corresponding to findings by *J. Hall & Krueger (2018)*, driver characteristics indicate predominant independence from common sources of employment discrimination such as age, educational attainment or Hukou status, which is likely to further accelerate

this effect (see subsection 2.4).[32] Both, low entry barriers and high volume elasticity are confirmed by *Fradkin et al. (2017*), analysing accommodation hosts on Airbnb. The results further suggest, that expected earnings of full-time ride-hailing drivers surpass the income level of significant shares in society, which corresponds to evidence from empirical work by *Berger, Frey, et al. (2018)* and *Cramer & Krueger (2016)*. All abovementioned arguments corroborate the aptitude of SE-platforms to empower work.

(2) The “race to the bottom” narrative, in contrast, emphasizes the alteration in working conditions as an intrinsic quality of platform-mediated labour organization. This perspective accredits the capacity of SE-services to empower labour but draws attention to the associated substantially deteriorating conditions of full-time workers in these arrangements. Contrary to part-time providers utilizing excess capacity, disenfranchised full-time labourers compete in a succession of short-term contracts for the next wedge of piecework remuneration (Collier et al., 2017). The trilateral relationship amongst providers, users and mediator reconfigures the contractual setup of labour: historical accomplishments of salaried work, such as fault tolerance, paid breaks and vacation, sick leave, health insurance and retirement savings are no longer available or the risks have been transferred from employers to workers (Collier et al., 2017; Gloss et al., 2016; Vallas, 2018). Moreover, the independent work arrangement lowers the bargaining power of labour due to collective action problems (Collier et al., 2017; Schor, 2017). The extent of this disparity is, of course, dependent on country-specific labour standards. The rudimentary social security system in China, for instance, eliminates the majority of differences since gradual advances to protect salaried workers in the recent decade are not available for relevant proportions of the society (J. Y. Chen, 2018; Z. Song, Storesletten, Wang, & Zilibotti, 2015). But beyond precarious labour standards in the service sector, which are observed and discussed since the 1980s, the large-scale shift towards a contingent workforce may cause further changes in the way how economic activities are prevailingly organized (Collier et al., 2017; Sundararajan, 2018). The advent of internet-

[32] Examining the presence of additional discrimination sources in the e-hailing sector (e.g. ethnicity-affiliation as indicated by *Schor & Attwood-Charles (2017)*) could provide an interesting extension for future work.

facilitated platforms disproportionally accelerates the diffusion of contingent work (Blinder, 2006; Collier et al., 2017; Katz & Krueger, 2019; Manyika et al., 2016). *Sundararajan (2018, p.489)* delineates this shift as a technology-driven continuation of developments in the nature of work towards a "crowd-based capitalism". During two generations of industrial revolutions, workers initially migrated from farms to manufacturing firms and, thereupon, from production plants to the service sector (Blinder, 2006). The proliferation of internet services has marked the advent of a third revolution, characterized by cheap and unresisted flows of information around the globe. This vastly expands the scope of tradable services and reduces transaction costs to infinitesimal scales, both reshaping barriers for the organisation of economic activities. Under this circumstances, the quintessential feature of "crowd-based capitalism" is a gradual alteration in the conventional provision of goods: the centralized and defined institution transforms towards a market hybrid, empowering decentralized microentrepreneurs to supply on-demand goods and services via direct peer-to-peer exchange (Blinder, 2006; Sundararajan, 2018). Findings of this study contribute to this perspective: 49% of the Didi-drivers work at least 4 hours per day, pointing to a social dependence of these individuals on platform earnings. The increase of self-employment relative

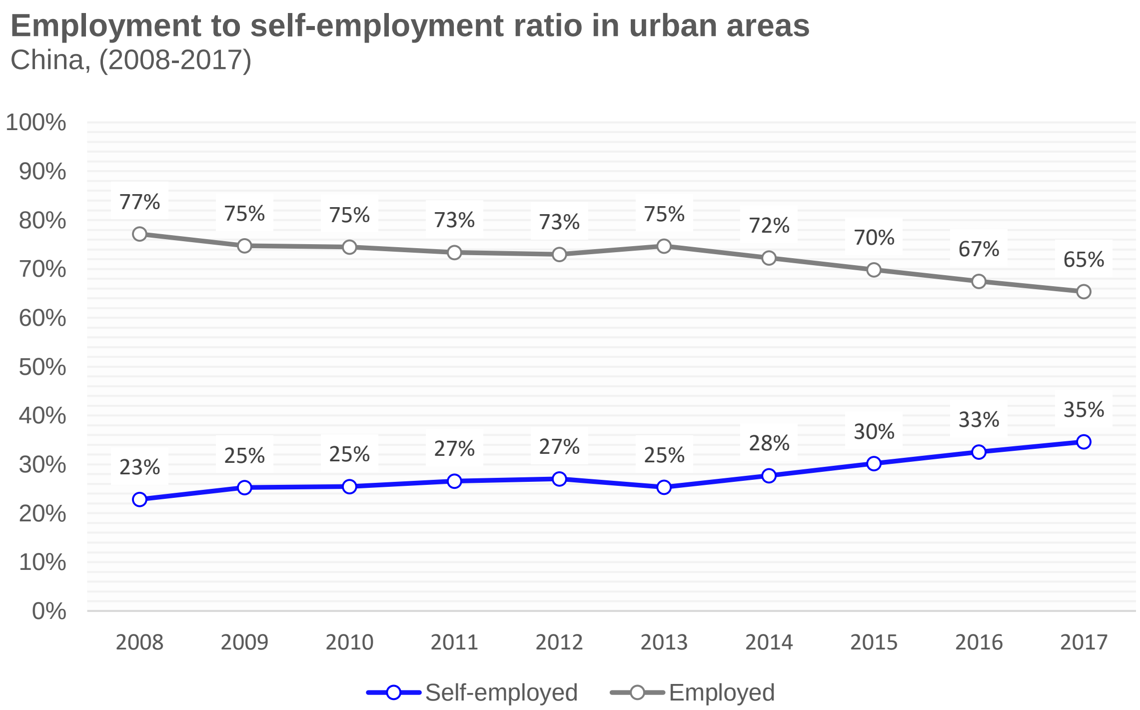

Illustration 19: Employment to self-employment ratio in urban areas (own illustration, data from NBS, 2019)

to population and economically active residents further indicates a transfer of labour supply from institutions to platforms. Eventually, the relevant magnitude of this effect is further corroborated by Illustration 19, visualizing the progressive convergence in the ratio of employed to self-employed individuals in China between 2008 and 2017.

Both of the described narratives are likely to be true in part. However, providing an profound answer as to which one dominates requires additional research, examining the obtained effects while carefully considering country-specific labour standards and general alterations of digital technology on the workforce (Avital et al., 2015; Sundararajan, 2018).

6.1.3 Discussion of ***hypothesis 3***

Two major results are obtained by the statistical formalization of *hypothesis 3* in a triple DID-design. First, the contrast of wage developments between mutual exclusive prosperity segments revealed a perceptible accession of income inequality in the period of observation. This outcome corresponds to a series of related academic work, exposing underlying determinants of inequality from the examination of the phenomenal industrialization in China during the past decades. The researchers shed light on the influence of structural discrimination between urban and rural areas (Hukou status) and the access to education, which makes inequality among Chinese residents the highest in the world (Xie & Zhou, 2014; Zhang, Wan, Wang, & Luo, 2017; Y. Zhou & Song, 2016; IMF, 2018). These insights refer to the second result of *hypothesis 3* described in subsection 5.3. Findings suggest an essential mitigation of distributional impacts in provinces with an exceptionally high market penetration of Didi. By intensifying competition for available labour supply, regardless of educational attainment or Hukou status, sharing platforms may contribute to a long-term harmonization of the significant disparity. Corresponding academic work validates the findings, indicating direct effects through disproportionally realized surplus gains of below-median income segments (Fraiberger & Sundararajan, 2015) and indirect cross-sector wage advances substantiated by the market launch of a SE-service (Z. Li et al., 2018). However, alternative examinations in other segments of the SE (e.g. qualitative interviews with Airbnb hosts) point to an exacerbating inequality at the bottom of the income distribution, suggesting that the abovementioned effect might not be a general epiphenomenon of the SE (Schor, 2017).[33] Encouraged by a decline of transaction costs, accommodation platforms, for instance, incentivise property owners to leverage their capacity in short-term rents, rather than providing it on the long-term rental market. A trend with positive accumulation effects for property owners but negative impacts on collective rental levels and therefore on tenants' disposable income (Ferreri & Sanyal, 2018). In addition, the spread of sharing businesses may have adverse effects on income levels of providers and workers in incumbent industries (Berger, Chen, et al., 2018; Zervas et al., 2013). Findings of this thesis indicate, that a unilateral dominance among these nonuniform impacts may crucially depend on the degree of local labour force incorporated in the platform-mediated provision of goods. The labour-intensive ride-hailing business spreads opportunity to a large number of workers facing precarious livelihoods in China (see subsection 2.4). Thereby, a significant drop in labour supply demonstrates a predominant indirect, cross-sector wage development. The scarcity of evidence on intersectoral effects of sharing platforms provides two insights: First, it opens a worthwhile avenue for future studies (e.g. with local Gini-coefficients). Second, it accentuates the paramount importance of incorporating indirect effects, which so far may not have been considered, when evaluating the phenomenon's overall socio-economic externalities.

6.1.4 Conclusion

Internet-facilitated sharing platforms have experienced meteoric growth in recent years, driven by both superior digital technology as well as a major shift in consumer behaviour, consolidated under the term "collaborative consumption". By exposing fundamental patterns of ride-hailing services on important macroeconomic indicators, this thesis contributes with empirical evidence of nontrivial socio-economic impacts. The obtained results are related to a set of previous academic research and enhance both the validity of available evidence as well as the creation of a holistic picture since a yet unobserved divergent fragment of the

[33] The findings of *Schor (2017)* are constructed on a relatively small sample of 43 qualitative interviews. Additional research is desirable to investigate the presence and magnitude of potential countervailing effects with more representative data.

SE is systematically assessed. In addition, the findings provide policy-makers with several advantageous insights, when designing an appropriate regulative framework.

A central question about the sharing economy is whether its emergence primarily constitutes a beneficial or detrimental technology-driven evolution for the various stakeholders. Although a generally valid answer to this question requires much more comprehensive evidence and information about country-specific factors, econometric approach and discussion within this thesis allow to draw some inferences about effects on the main stakeholders: (1) consumers are the clear beneficiaries as SE-services not only augment existing options by a flexible, convenient and versatile offer but also reduce price levels. (2) Providers face controversy effects. On the one hand, SE-platforms spread largely unresisted opportunities for flexible and viable working. As contrasted in subsection 6.1.2, providers' associated risks vary essentially between part- and full-time workers. On the other hand, characteristics of platform-mediated contingent work may constitute a substantial deterioration of working conditions, depending on country-specific labour standards. Hence, a broad spectrum of researchers agree that the interaction of mediator and provider is a critical lever for targeted regulation, in order to prevent platforms from gaining superior market power over workers (e.g. B. Cohen & Kietzmann, 2014; Edelman & Geradin, 2015; Ganapati & Reddick, 2018; Kenney & Zysman, 2016; Vallas, 2018). (3) Competing incumbent corporations and workers within these industries are confronted with declining revenues and wages, respectively. Companies, which are not immediate substitutes of SE-services may nevertheless be confronted with increasing competitive pressure on the labour supply if their business activity particularly depends on low-income/low-skilled workers. However, partnerships with SE-marketplaces may also increase manufacturers' revenues by stimulating the production of goods for platform-mediated rental supply (Fraiberger & Sundararajan, 2015; Guo et al., 2018). (4) Society as a whole can benefit from progress in urban sustainability, in case improvements are not outpaced by a disproportionate increase in consumption. Moreover, sharing platforms can contribute to the harmonisation of income-disparities, if the provision of the respective good is characterized by a labour-intensive procedure. The SE can generate essential socio-economic advantages and change the quintessential organisation of economic activities within the society. Its success, however, is indissociable connected with targeted (political) interventions to mitigate unintended negative externalities. Eventually, the future development of the sector will expose whether the proponents' promise of a “crowd-based capitalism” effectively combines efficiency gains with positive influences on collective equality, trust and connectedness.

6.2 Limitations

6.2.1 Preliminary note

This work is, of course, subject to several limitations, which offer potential sources of future investigations. In the consecutive subsections, an overview of possible factors affecting the explanatory power of the obtained results is provided.

6.2.2 Generalizability

As discussed earlier, constraints such as the scarcity of available data or significant disparities of corporate characteristics substantiate a focus on single countries, markets and corporations in empirical examinations on impacts of emerging sharing platforms. The widespread approach, however, markedly limits the explanatory power of single empirical studies in terms of generalization. This restriction also applies to results obtained in this thesis. Internet-facilitated ride-hailing is only a submultiple within the plenitude of sharing economy business models, each of which being characterized by individual deviations. Moreover, Didi Chuxing has its unique business characteristics and generates the vast majority of its revenues in China. Hence, care must be taken when extrapolating the results to other SE-markets, countries or companies without further considerations. Such considerations should take into account the company concerned and country-specific market characteristics, regulative criteria and industry policies of China (Lo & Wu, 2014). This thesis is not intended to identify the overall impacts of SE-platforms on economy and society, but aims to contribute with a heuristically useful step towards a holistic picture of the phenomenon as it is currently emerging from a growing body of literature (e.g. Berger, Chen, et al., 2018; Cramer & Krueger, 2016; Ferreri & Sanyal, 2018; Mittendorf, 2017). Thus, further research is required to replicate and validate the applied research design with either alternative sharing economy services or other countries (or both) to improve its generalizability.

6.2.3 Selected data sets

Several limitations occur with regards to the selected data. The sharing economy is a relatively new phenomenon – although its most recognizable corporations gradually achieved a similar spatial proliferation and market adoption as long-established multinational enterprises. The observable period since the inception of first sharing platforms in 2008 is limited to a maximum of 10 years; hence, examinations of longer-term consequences are not yet feasible (J. Hall & Krueger, 2018; Z. Li et al., 2018). This study covers a 10-year period incorporating a set of observations prior to Didi's market launch in 2012. The intuition behind this approach is to balance possible pre-existing trends in the variables of interest. However, the number of periods with observable market activity of Didi is limited to 5 years. Future research using extended panel observations, when they become available, are worth to pursue in order to examine whether results obtained in this work are consistent over a longer period of time. The reliability of the data sources utilized in this thesis could not be validated independently by the author. The discussion on the aptitude of official unemployment rates exemplifies, that all variables are determined to the best knowledge of the author, using attached documentation and information files by the institutions as well as independent studies (e.g. Giles, Park, & Zhang, 2005; Gustafsson, Li, & Sato, 2014; Holz, 2013; Koch-Weser, 2013). However, not all sources of distortions may have been identified and thoroughly purged out. Nevertheless, it is unlikely that findings are significantly biased due to the presence of serious distortions, as data from the accordant institutions have been analyzed in a large number of previous studies. Therefore, it can reasonably be assumed that quality standards have already been critically reviewed by previous scholars. With respect to CFPS-data, the final extent of the adjusted sample covering 2.792 individuals corresponds to a proportion of 0,0002% of China's total population in 2016 (Worldbank, 2019e). Although representative in urban areas, future research evaluating larger sample sets can provide additional evidence to further corroborate the verified hypotheses. Alternative social survey data provided by several Chinese institutions, e.g.

the China Institute for Income Distribution (CHIPS), the Chinese General Social Survey (CGSS) or the China Household Finance Survey (CHFS), offer potentially fruitful avenues for future work as soon as data sets of the relevant period will become available.[34]

6.2.4 Approximation validity of Baidu Index

In a pioneering approach, this thesis exploits search engine volume of relevant keywords to approximate the market adoption of SE-businesses in China. Validity examinations on the accuracy of this proxy are conducted using static moments. The causal inference is further corroborated by the reference to a set of related empirical examinations. However, an approximation is typically less accurate than actual data. Considering the small magnitude of Baidu Index with the utilized keywords, future studies could enhance the approximation quality by extending the keywords in a first step, to consider a broader number of second-tier ride-hailing platforms such as Shouqi, Caocao, Meituan-Dianping or Yidao. The consistency of the obtained results is unlikely to be significantly affected since the trivial market shares and negligible growth of these players only marginally influence the overall dynamic of the Chinese e-hailing sector (see illustration 5). In a second step, results could be verified utilizing actual continuous data, e.g. the number of daily users and drivers, when such figures become available. Rumours on Didi's IPO in 2019 have not yet been officially confirmed by the company (The Wall Street Journal, 2018). However, in case a public listing is placed in the near future, it constitutes a fundamental turn, regarding the public transparency of business figures since the company will be obliged to correspond to disclosure requirements. In turn, researchers will be able to examine the socio-economic impacts of this digital innovation in more detail.

[34] As of May 2019, the most recent year of observation in the abovementioned social surveys is 2013.

7 Appendix

I. Determinants of private car possession in China

31 provinces, (2008-2017)

	Outcome: Private car possession
Resident population	**0,12*** (0,05)
Urbanisation ratio (%)	**-0,26** (0,28)
Gross regional product	**0,02***** (0,001)
Number of taxicabs	**0,006***** (0,002)
Transit passenger kilometres	**-0,13***** (0,02)
Years of observation	2008-2017
Observations	310
Groups	31
P-value model	*p < 0,001*
Adjusted R^2	*0,88*
Heteroscedasticity (Breusch-Pagan)	*YES*
Serial correlation (Breusch-Godfrey/Wooldridge)	*YES*
Model (Hausman)	Fixed-effects

Notes: Robust standard errors are in parentheses (sandwich estimator). Statistical significance is denoted by: *p < 0,01*** p < 0,05** p < 0,1**.

Table 9: Determinants of private car possession in China

II. Determinants of ride-hailing driver growth in China

31 provinces, (2017)

	Outcome: Driver growth (YOY, %)
Intercept	**374,03***** (130,80)
Resident population (ln)	**19,81***** (6,12)
Gross regional product (ln)	**-24,71***** (5,83)
Year of observation	2017
Observations	31
P-value model	*p < 0,01*
Adjusted R^2	*0,02*
Heteroscedasticity (Breusch-Pagan)	*YES*
Variance inflation factor (max.)	*3,53*

Notes: Robust standard errors are in parentheses. Statistical significance is denoted by: *p < 0,01*** p < 0,05** p < 0,1**.

Table 10: Determinants of ride-hailing driver growth in China

III. Correlation of driver growth and google trends volume in US-cities

Illustration 20: Correlation of driver growth and google trends volume in US-cities (J. D. Hall et al., 2018)

IV. Web scrawling of Baidu Index

Baidu Index provides a visual presentation of the keyword search volume, which can be spatially clustered for the requested period. However, meta-data cannot be downloaded without additional fees. Thus, a python code was generated by Ms. Xin Yue to crawl the generated web content from the Baidu server. A structural instruction on the applied code can be found on:

https://edmundmartin.com/scraping-baidu-with-python/

https://github.com/brightgems/fetch_baidu_index

V. Didi’s driver income average calculation:

The report published by Didi Chuxing in June 2017 reveals average total incomes of drivers as displayed by illustration 21:

Total Income Distribution of Didi Chuxing Drivers in China (%)
Proportions in %, sections in Chinese RMB, (2016)

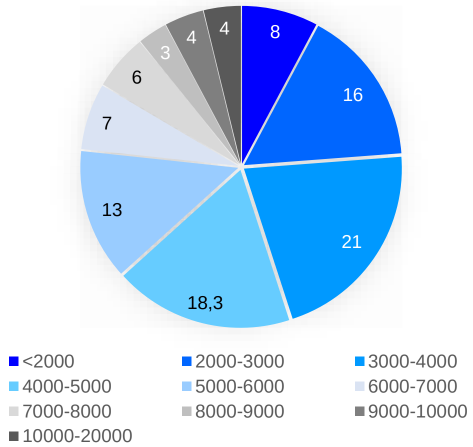

Illustration 21: Total Income Distribution of Didi Chuxing Drivers in China (%) (own illustration, data from Didi Chuxing, 2017).

The presumed compensation effect formulated in *hypothesis 3* as a result of sector transition is likely to be observable when full-time employees resign their primary work due to Didi Chuxing's viable job opportunity. The idea behind this assumption derives from the fact, that the labour supply in contracted primary jobs remain detached when people decide to take up an additional part-time job. Hence, full-time earnings of Didi drivers are relevant for the estimation of an expected income threshold, which is likely to trigger occupational change of extrinsically motivated workers. Considering that hourly wage and number of hours worked are almost independent, 51% of drivers whose daily working hours indicate a part-time activity are omitted from the further estimation. A weighted arithmetic mean is calculated to derive the average annual income among the remaining categories of the income statement. This approach results in an estimated annual average income of RMB 41.612. Contrasted to the pre-tax average income in urban areas of RMB 67.569 in 2016, the gross income of full-time Didi drivers corresponds to a relative share of 68% (NBS, 2019).

VI. Annual descriptive statistics (NPS data, 2009-2016)

31 provinces (2009)

Variable:	Mean	SD	Min.	Max.
Consumer price index (transport)	99,3	1,3	96,8	102,7
Number of self-employed in transport, storage and post	104.067	109.135	6.400	591.300
Baidu Index (average p.d.)	0	0	0	0
Fuel price (index)	112,7	1,9	108,9	115,8
Passenger traffic (in million)	952,9	866,5	78,4	4.189,4
Public transport price level (index)	101,0	1,6	96,6	104,3
Economically active population (in % of total population)	74	3	67	80
Number of taxicabs	31.341	20.076	1.544	77.295
Resident population (in million)	42,7	27,0	3,0	101,3

Note: Observations = 31

31 provinces (2010)

Variable:	Mean	SD	Min.	Max.
Consumer price index (transport)	101,4	2,3	98,4	110,5
Number of self-employed in transport, storage and post	104.171	93.420	6.700	646.600
Baidu Index (average p.d.)	0	0	0	0
Fuel price (index)	105,5	3,3	100,9	113,0
Passenger traffic (in million)	1.064,0	952,5	81,7	4.561,4
Public transport price level (index)	101,7	2,2	97,1	105,4
Economically active population (in % of total population)	74,3	3,5	66,8	81,3
Number of taxicabs	31.812	20.098	1.375	79.890
Resident population (in million)	43,0	27,2	3,0	104,4

Note: Observations = 31

31 provinces (2011)

Variable:	Mean	SD	Min.	Max.
Consumer price index (transport)	104,5	2,7	100,2	112,3
Number of self-employed in transport, storage and post	112.487	101.613	8.200	511.200
Baidu Index (average p.d.)	0	0	0	0
Fuel price (index)	117,3	4,1	111,0	125,4
Passenger traffic (in million)	1.228,1	1.045,7	37,4	5.106,5
Public transport price level (index)	103,0	3,7	89,9	108,9
Economically active population (in % of total population)	74,9	3,7	89,9	108,9
Number of taxicabs	32.332	19.991	1.379	79.248
Resident population (in million)	43,2	27,2	3,0	105,1

Note: Observations = 31

31 provinces (2012)

Variable:	Mean	SD	Min.	Max.
Consumer price index (transport)	106,0	3,1	100,8	113,1
Number of self-employed in transport, storage and post	185.135	232.702	8.300	119.300
Baidu Index (average p.d.)	0	0	0	0
Fuel price (index)	130,5	4,9	122,2	140,8
Passenger traffic (in million)	1.216,8	1.154,2	38,5	5.742,7
Public transport price level (index)	105,0	4,7	87,4	112,7
Economically active population (in % of total population)	74,5	3,8	67,9	82,5
Number of taxicabs	33.118	19.988	1.378	79.868
Resident population (in million)	43,5	27,3	3,1	105,9

Note: Observations = 31

31 provinces (2013)

Variable:	Mean	SD	Min.	Max.
Consumer price index (transport)	106,4	3,5	100,1	113,8
Number of self-employed in transport, storage and post	124.209	104.046	5.400	464.400
Baidu Index (average p.d.)	11,5	10,2	0,0	37,0
Fuel price (index)	134,1	5,1	125,3	144,8
Passenger traffic (in million)	673,4	473,4	14,6	1.597,3
Public transport price level (index)	107,2	5,8	88,3	119,1
Economically active population (in % of total population)	74,3	3,4	68,6	81,5
Number of taxicabs	33.986	19.946	1.354	79.607
Resident population (in million)	43,7	27,4	3,1	106,4

Notes: Observations = 31

31 provinces (2014)

Variable:	Mean	SD	Min.	Max.
Consumer price index (transport)	106,9	4,0	99,8	114,1
Number of self-employed in transport, storage and post	133.051	111.817	5.700	499.900
Baidu Index (average p.d.)	115,1	69,6	1,0	269,0
Fuel price (index)	133,2	4,9	123,7	143,3
Passenger traffic (in million)	700,1	502,1	15,7	1.807,9
Public transport price level (index)	108,6	6,7	88,3	125,0
Economically active population (in % of total population)	74,0	3,4	68,6	81,3
Number of taxicabs	34.657	20.230	1.554	80.951
Resident population (in million)	44,0	27,5	3,2	107,2

Note: Observations = 31

31 provinces (2015)

Variable:	Mean	SD	Min.	Max.
Consumer price index (transport)	104,8	5,0	94,5	116,1
Number of self-employed in transport, storage and post	130.296	119.317	5.800	475.500
Baidu Index (average p.d.)	259	209	12	938
Fuel price (index)	131,8	4,6	122,4	139,3
Passenger traffic (in million)	612,8	407,4	10,9	1.383.1
Public transport price level (index)	110,1	7,4	88,3	125,7
Economically active population (in % of total population)	73,4	3,2	67,6	79,6
Number of taxi cabs	35.228,5	20.246,8	1.882,0	80.997,0
Resident population (in million)	44,2	27,7	3,2	108,5

Note: Observations = 31

31 provinces (2016)

Variable:	Mean	SD	Min.	Max.
Consumer price index (transport)	103,2	5,0	93,3	112,8
Number of self-employed in transport, storage and post	149.725,8	130.484,1	9.600,0	508.900,0
Baidu Index (average p.d.)	439,6	308,1	69,0	1.275,0
Fuel price (index)	111,8	4,0	103,7	122,3
Passenger traffic (in million)	597,2	393,8	11,6	1.335,8
Public transport price level (index)	114,8	15,5	88,4	187,3
Economically active population (in % of total population)	73,0	3,0	68,1	78,0
Number of taxi cabs	35.566,5	20.105,8	1.882,0	80.743,0
Resident population (in million)	44,5	28,0	3,3	110,0

Note: Observations = 31

Table 11: Annual descriptive statistics (NPS data, 2009-2016)

8 Literature, references and data

8.1 Data sources

8.1.1 Statista

Statista has been approached via the access of Zeppelin University.

Statista (2017): Meet DiDi: China's Answer to Uber

Statista (2019a): Ride Hailing – Statista Digital Market Outlook

Statista (2019b): Ride Hailing – Global Consumer Survey

Statista (2019c): Search engine market shares in China in 1st quarter 2018, by company

Statista (2019d): Average hourly earnings of rideshare drivers in the United States as of February 2018, by number of trips (in U.S. dollars)

8.1.2 Worldbank

Worldbank open data terminal has been approached via:

https://data.worldbank.org/

Worldbank (2019a): World's total population, accessed on 26.03.2019 via:

https://data.worldbank.org/indicator/SP.POP.TOTL

Worldbank (2019b): World's total working age population, accessed on 26.03.2019 via:

https://data.worldbank.org/indicator/sp.pop.1564.to

Worldbank (2019c): World's GDP per capita, accessed on 14.04.2019 via:

https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=MX

Worldbank (2019d): Unemployment, total (% of total labor force), accessed on 19.04.2019 via:

https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS?end=2018&start=2008&view=chart

Worldbank (2019e): China, Population, total, accessed on 26.05.2019 via:

https://data.worldbank.org/indicator/SP.POP.TOTL?locations=CN

8.1.3 National Bureau of Statistics, China

The National Bureau of Statistics (China) data terminal has been approached via:

http://data.stats.gov.cn/english/index.htm

8.1.4 China Family Panel Study

The China Family Panel Survey datasets are available on the main website:

www.isss.pku.edu.cn/cfps/

CFPS (2019): About CFPS, accessed on 16.04.2019 via:

www.isss.pku.edu.cn/cfps/

8.1.5 United States Department of Labor – Bureau of Labor Statistics

LBS open data terminal has been approached via:

https://www.bls.gov/data/

LBS (2019): Average hourly employment

8.2 Literature and journals

Abelson, P. (2018). The High Cost of Taxi Regulation, with Special Reference to Sydney. *Agenda - A Journal of Policy Analysis and Reform*. https://doi.org/10.22459/ag.17.02.2010.03

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9 Declaration of authorship

I hereby declare that the thesis submitted is my own unaided work. All direct or indirect sources used are acknowledged as references.

I am aware that this paper in digital form can be examined for the use of unauthorized aid and in order to determine whether the paper as a whole or parts incorporated in it may be deemed as plagiarism.

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Friedrichshafen, 05th June 2019

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Ehrenwörtliche Erklärung

Ich erkläre hiermit ehrenwörtlich, dass ich die vorliegende Masterarbeit mit dem Thema:

„Beyond digital disruption: Estimating the socio-economic impacts of the sharing economy – Evidence from China“

selbstständig und ohne fremde Hilfe angefertigt habe.

Die Übernahme wörtlicher Zitate sowie die Verwendung der Gedanken anderer Autoren habe ich an den entsprechenden Stellen der Arbeit kenntlich gemacht.

Ich bin mir bewusst, dass eine falsche Erklärung rechtliche Folgen haben wird.

Friedrichshafen, 05.06.2019

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