Analysing long-term effects of the Covid-19 pandemic on last-mile delivery traffic using an agent-based travel demand model

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Abstract

E-commerce demand has increased steadily over the last decades and this trend has accelerated even more since the start of the Covid-19 pandemic. This entailed that user groups such as older people who previously only shopped in-store were incited to shop online to reduce risk of infection leading some to switch to online shopping as the main shopping channel. This study analyses the long-term effects of increased online shopping and subsequent delivery demand due to the Covid-19 pandemic using an agent-based travel demand model. We analyse the simulation of two scenarios for the model area Karlsruhe, Germany: one scenario simulates the parcel delivery demand before the pandemic and the other scenario simulates the demand during the pandemic of the synthetic population. Our results show that there have been shifts in both socio-demographic characteristics of online shoppers and spatial distribution of parcel delivery demand induced by the Covid-19 pandemic. The scenario simulation based on the pandemic related data shows that not only the influence of income has shifted but also the effects of age on e-commerce activity has changed due to the pandemic. The findings are of interest to transport planners and delivery service providers as they highlight the importance of recognising that the Covid-19 pandemic not only induced a shift in socio-demographic profiles of online shoppers but that this shift also entails a change in the spatial distribution of parcel deliveries.

1 Introduction

E-commerce is one of the fastest growing market segments and online shopping has increased steadily over the last years [1]. This trend has accelerated even more since the start of the Covid-19 pandemic, as policy measures included temporary closings of retail stores and general stay-at-home recommendations to decrease the spread of the virus. While many of the behavioural changes induced by the pandemic are expected to return to normal, the sudden disruption of daily routines may have lead people to change their habits which are usually hard to break out of [2]. In the case of e-commerce, this entailed that user groups such as older people who previously only shopped in-store were incited to shop online to reduce risk of infection leading some to switch to online shopping as their main shopping channel [3, 4]. While the Covid-19 pandemic has highlighted generational differences in consumer shopping behaviour [5], it forced consumers to adopt new technologies in order to reduce the risk of infection [6]. Although many studies highlight managerial implications of the changes in consumption patterns, no study has analysed the effect of shifts in e-commerce activity induced by the pandemic on parcel delivery demand.

This study analyses the long-term effects of increased online shopping and subsequent delivery demand due to the Covid-19 pandemic using the agent-based travel demand model *mobiTopp* [7, 8]

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and the urban logistics model extension *logiTopp* [9, 10]. To analyse the long-term effects of the Covid-19 pandemic on e-commerce demand and subsequent delivery traffic, we simulated two scenarios for the model area Karlsruhe, Germany with a synthetic population of 303,809 agents: one scenario simulates the parcel delivery demand before the pandemic and the other scenario simulates the demand during the pandemic. The travel demand for both scenarios is based on pre-pandemic data.

The rest of this paper is structured as follows: We first provide an overview over the data on which our analyses are based. Subsequently, we present the modelling framework mobiTopp and it's last mile logistics extension logiTopp. We go on to present and discuss the results of the scenario simulations and conclude the paper with overarching implications.

2 Materials and Methods

In this section, we provide an overview over the data used to model the behavioural differences in online shopping behaviour before and during the Covid-19 pandemic. Subsequently, we describe the modelling framework we used for our analyses.

2.1 Data

The data for the parcel order and destination choice models was collected using a survey among participants in Germany. Participants were recruited through an online access panel and the sample was stratified by age, gender, and population of the place of residence. The survey was completed by a net sample of 1,002 participants. The survey included questions regarding

- socio-demographic information,
- mode choice behaviour,
- weekly activity patterns, and
- online shopping.

For all questions except those regarding socio-demographics, we asked participants to reflect on their behaviour during the Covid-19 pandemic and retrospectively provide information of the time before the pandemic. For the purpose of this study, we focused on the socio-demographic variables and changes in online shopping behaviour.

Figure 1 shows the changes in online shopping frequency from the time before the pandemic to the time during the pandemic. From the graph we can see, that respondents considerably increased the frequency with which they shopped online. Overall, only a minority (8%) of respondents decreased the frequency of online shopping, whereas a third increased the frequency. While the share of respondents shopping online on a daily basis only increased by 1%, a considerable change can be detected for those who shopped online on a weekly basis: Before the Covid-19 pandemic, 13% of respondents attested that they shopped online 1 to 3 times a week. This share almost doubled to 25% during the pandemic.

The summary of socio-demographic information of the entire survey sample and grouped by online shoppers vs. non online shoppers is presented in Table 1. The results show that there was a shift in all socio-demographic characteristics of online shoppers, with the most prominent changes in the ratio of those aged between 25-44 years and over 65 years.

2.2 Estimation of Online Shopping Demand

The survey data is used to create the online shopping demand as the number of parcels per week and modelled agent using a poisson regression model. To account for the overdispersion in the data,

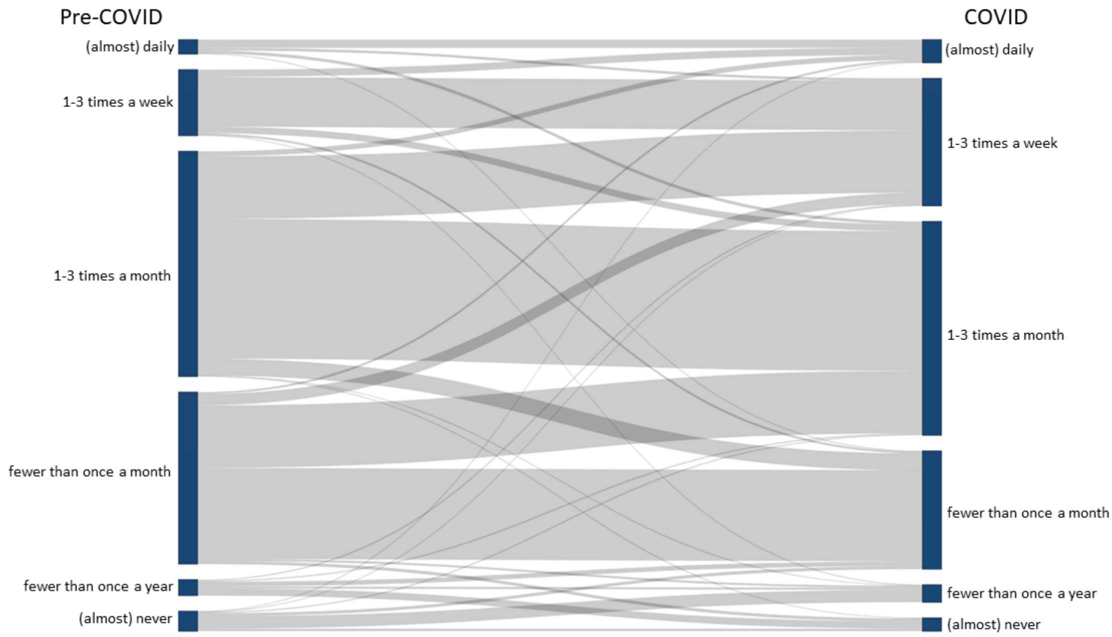

Figure 1: Changes in online shopping frequency before and during the Covid-19 pandemic.

	survey	pre-covid		during covid	
		OS	non-OS	OS	non-OS
gender					
female	50%	38%	62%	49%	51%
male	50%	38%	62%	51%	49%
age					
under 25 years old	10%	53%	47%	62%	38%
25 - under 45 years old	31%	47%	53%	61%	39%
45 - under 65 years old	41%	33%	67%	44%	56%
over 65 years old	18%	25%	75%	38%	62%
income					
below 2,500€	45%	33%	67%	44%	56%
2,500 - below 4,000€	26%	38%	62%	52%	48%
4,000€ and more	28%	45%	55%	57%	43%
work status					
not working	41%	31%	69%	44%	56%
working	59%	58%	42%	54%	46%

Table 1: Socio-demographic information of online shoppers (OS) vs. non-OS pre-covid and during covid

we opted for a negative binomial generalised linear model. For the estimation, we used the function *glm.nb* from the R package *MASS* [11].

To simulate and analyse these shifts between the two scenarios, we estimated two sets of parameters based on the responses regarding online shopping frequency before and during the Covid-19 pandemic. While the modelling framework is designed such that activity patterns can be regarded in the online order model, the Covid-19 pandemic induced changes in activity patterns of participants to a degree where it is insensible to account for them in a model aimed at simulating the post-pandemic state. We therefore only included socio-demographic characteristics as independent variables to determine online shopping frequency as the dependent variable. As this study focuses on the application of the model and the effects that can be discerned, presentation of the parameters is outside the scope of this paper, however, we intend to present the underlying behavioural models of logiTopp in a later publication. Currently, the parameters are available upon request to the corresponding author. The integration of the model of online shopping demand into the modelling framework is described in the following section.

2.3 Modelling Framework

To analyse the changes in online shopping behaviour induced by the Covid-19 pandemic on last-mile deliveries, we integrated the behavioural changes into the modelling framework *mobiTopp* and it's last-mile logistics extension *logiTopp* [9, 10]. This section provides a concise overview of the modelling framework.

mobiTopp

The travel demand modelling framework *mobiTopp* [7, 8] consists of two modules: a long- and a short-term module. In the long-term module, a synthetic population of households and their individual agents are generated. Each agent is assigned socio-demographic attributes including: age, gender, work status, highest degree of education, income, place of work/education, drivers license, commuter ticket and membership to mobility service providers like bike-sharing or car-sharing. Households are assigned household-attributes accordingly including: a number of household members, a number of cars, a home location and a net income. To ensure intrapersonal and intra-household consistency, households and persons are drawn from a population pool provided by the German Mobility Panel [12] which is a national household travel survey. Additionally, activity schedules are generated for each agent including work, business, education, shopping, leisure, service and home activities. These activity schedules contain activities for the entire simulation period of one week [13].

All trips towards these activities are simulated in the short-term module. For each new activity, a destination and a travel mode are chosen. The simulated travel times may differ from the estimated travel times used in the long-term module when planning an activity schedule. Therefore, the activity schedule can be updated before each trip to consider the actual travel times. These steps are repeated for each activity and are simulated for all agents simultaneously.

logiTopp

We integrate last-mile deliveries into the *mobiTopp* framework in the form of the logistics extension called *logiTopp* [9, 10]. *logiTopp* takes advantage of *mobiTopp*'s agent based approach and the simultaneous simulation and interaction of these agents to model parcel orders of individual agents and simulate their last-mile delivery. *logiTopp* is implemented in Java and available as an open-source extension of *mobiTopp* on GitHub [14]. *logiTopp* mostly extends the short-term module of *mobiTopp*. Before the simulation of the short-term module starts, delivery agents are selected from the population and assigned to one of the modelled distribution centres (DCs). In this way, both the delivery agent's private and commercial trips are simulated.

To determine the parcel demand and the specific attributes of these parcels, a parcel demand model is applied to each potential recipient. *logiTopp* supports both private persons and businesses as recipients, however, in this paper we will focus on the demand of private parcels (b2c). As a first step, the parcel demand model determines the number of parcels expected by an agent for the simulated time period of one week. The specific attributes of these parcels are determined by the following steps: Selecting a delivery location (home, work or parcel locker); selecting a "Courier, Express and Parcel" service provider (CEPSP); selecting a DC from where it will be delivered and selecting an arrival date at the DC.

The model steps used in this study are shown in Figure 2 on the left. The step 'choose number of parcels' is implemented by the means of the model described above (2.2). The delivery location is selected based on a discrete choice model similar to the one described in [9, 10] The DC and the corresponding CEPSP are selected based on their relative share in the survey area. The arrival date is selected equally distributed throughout the week, except for Sundays, on which no parcels are distributed in Germany.

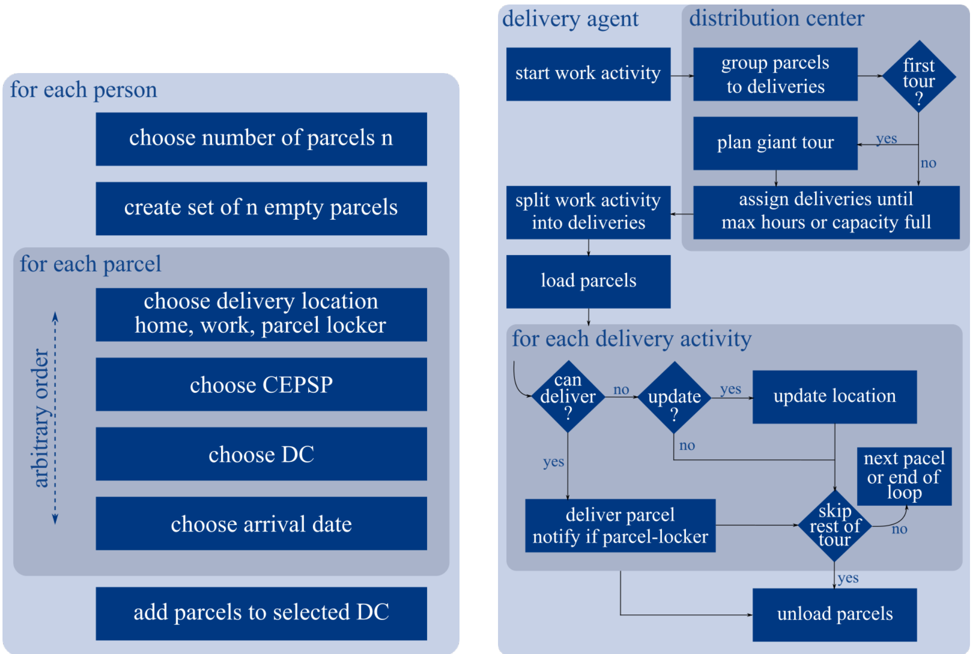

Figure 2: Steps of the parcel demand model on the left; Steps of the delivery process on the right.

The parcel demand and the delivery agents are generated before the actual simulation of trips and activities. This simulation is carried out by the *mobiTopp* framework. The *logiTopp* extension comes into play, once a delivery agent arrives at their workplace (a DC). The model components used during the simulation are shown on the right in Figure 2. Upon arrival at the DC, the agent's delivery tour is planned. We use a route first, cluster second heuristic [15] to approximate optimal delivery tours by using a 2-approximation TSP (travelling salesperson problem) algorithm provided by the JGraphT library [16]. The delivery agent's work activity is split into multiple delivery activities in the planned order. They are enclosed by an initial 'load' activity and a final 'unload' activity. These activities and the intermediate trips are simulated simultaneously to those of private agents.

Each DC specifies two rules to define under which conditions parcels can be delivered and what happens if a parcel cannot be served. In our model, home deliveries can be received by the recipient themselves, an other household member or a neighbour. Deliveries to parcel lockers are always successful, while work deliveries can only be received personally. Checking the presence and absence of the recipient as well as the other household members or neighbors is possible due to the agent based nature of *mobiTopp* and the simultaneous simulation of all agents and their activities. In case of an unsuccessful delivery, the DC can decide to update the parcel's destination to a parcel locker. A common policy in our survey area are three delivery attempts, however, two CEPSP only perform one delivery attempt, which is reflected by the individual policies per DC in our model.

3 Results and Discussion

In this section, we describe the model results of the two simulation scenarios. We applied the previously described modelling framework to Karlsruhe, a city in the Southwest of Germany. The synthetic population includes 303,808 agents in 170,013 households. The results of the two simulated scenarios are summarised in table 2.

	pre-covid	covid
number of parcels	211,284	232,291
online shopping participants	121,436	131,593
distribution of parcel order frequency		
1 parcel	59%	57%
2 parcels	24%	26%
3 parcels	9%	10%
4 parcels	4%	4%
5 parcels	2%	2%
6 or more parcels	1%	1%
number of delivery vehicles	196	200

Table 2: Simulation results by scenario

From the table we can see that in the scenario based on the Covid-19 data, both the number of online shopping participants and the number of parcels increased. The number of simulated parcels increased by 9.94%, while the number of agents participating in online shopping increased slightly less by 8.36%, indicating that the online shopping frequency per online shopper changed. These changes are discernible in the distribution of parcel order frequency: Regarding all online shopping participants, the number of those who only ordered one parcel during the simulated week decreased by 2% in the Covid-19 based scenario, while those ordering two or three parcels increased slightly. The number of vehicles needed to deliver the simulated parcels increased by 2%.

The magnitude of the increase in parcel demand between the two scenarios is consistent with the report presented by the German federal association parcel & express logistics who reported an increase of 10% in delivered parcels induced by the Covid-19 pandemic [17]. The relatively small increase in delivery vehicles is somewhat surprising, but can be explained by the fact that the capacity of the vehicles is - as of yet - not based on shipment sizes and thus does not necessarily reflect the actual number of vehicles but rather a magnitude of vehicles needed.

Because we account for socio-demographic variables in the parcel order model, we are able to analyse these characteristics for agents who order parcels in the simulation. Figure 3 shows the socio-demographic variables gender, age group, income group and work status for the pre-Covid simulation, the scenario based on Covid-19 data as well as the entire synthetic population (online shoppers and non-online shoppers). Overall, the shifts between socio-demographic variables of online shoppers in the simulation are similar to those from the survey data (see Table 1) confirming the general validity of the choice models.

Considering the gender of online shoppers, there is no discernible difference between the two simulations as in both cases males are slightly more likely to order and receive a parcel in the simulation week compared to the entire population. The barplot considering the distribution among the different age groups shows that in the Covid-19 based scenario, especially those over the age of 65 years are more likely to shop online compared to the pre-pandemic scenario. By contrast, the opposite holds true for the age group of those under 25 years old. Considering middle two age groups, no considerable changes in their percentage shares can be identified. This indicates, that new online shoppers are older and previously did not feel the need to shop online instead of in-store. Considering the income group of online shoppers, the graph shows that the Covid-19 pandemic shifted towards those with a lower income. For both scenarios but for the pre-pandemic scenario especially, those shopping online are present with a disproportional high income compared to the rest of the population. The graph considering the work status of agents who ordered and received a parcel in the simulated week shows that there is neither a difference in distributions between the scenarios nor the overall population.

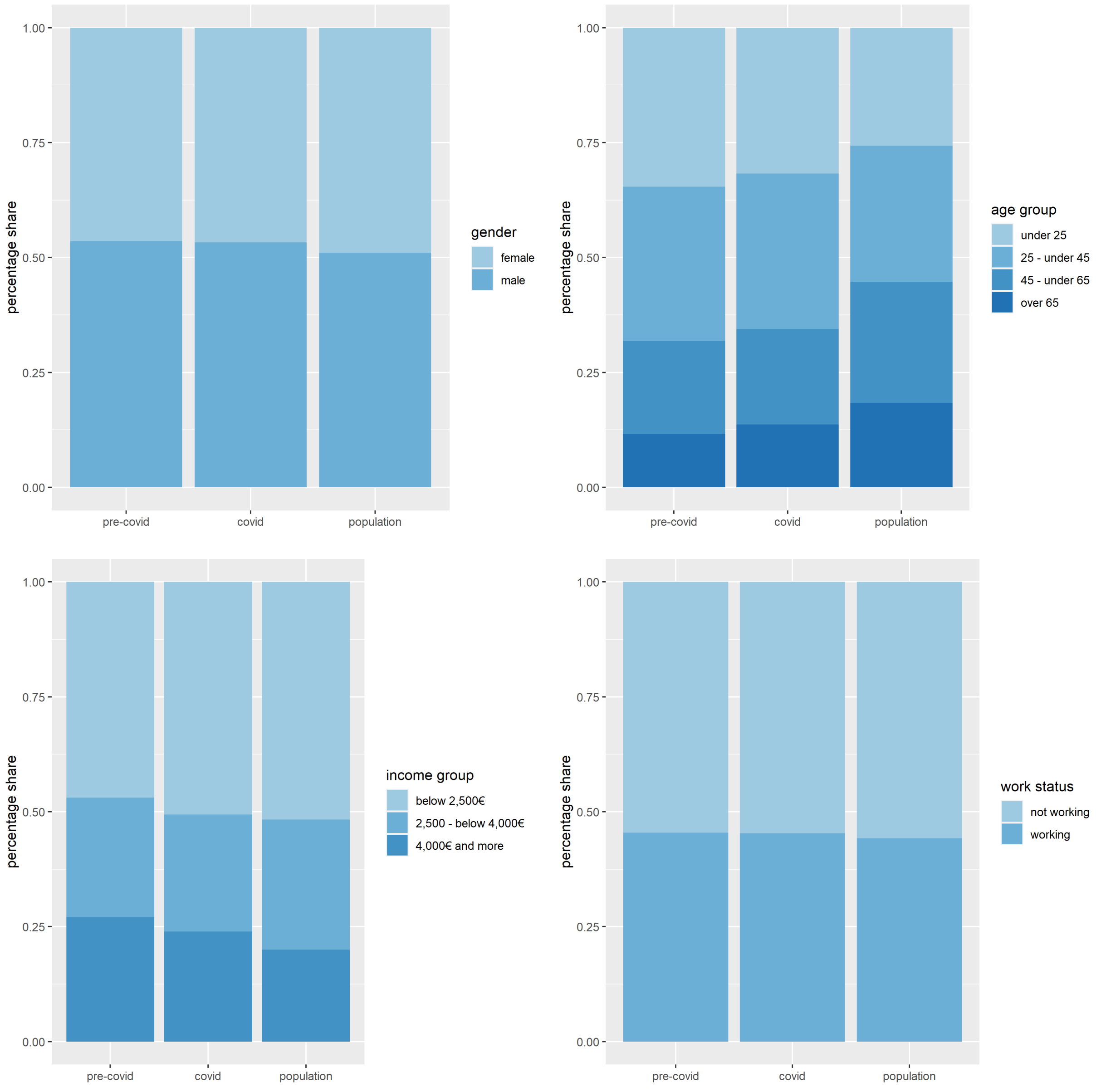

Figure 3: Socio-demographics of online shopping agents by scenario: gender (top left), age group (top right), income group (bottom left), work status (bottom right)

To assess if the changes in socio-demographics of online shoppers also result in different delivery areas, we also analysed changes in the spatial distribution of deliveries. Figure 4 shows the absolute difference of parcel orders and subsequent deliveries in the travel analysis zones (TAZs) between the two scenarios. A positive value (bright green to yellow) means that more parcels were ordered in the Covid-19 scenario. From the graph we can see that especially in the North, the Northeast and the South of the city there are several TAZs in which deliveries increased in the Covid-19 scenario compared to the pre-pandemic scenario. Considering the age distribution of the respective city districts, the delivery increase in the Northern and Southern parts of the city can be traced back to the fact that in these city districts, there is a high prevalence of older inhabitants. Analysis of the Northeastern part of the city revealed that the increase in online shopping activity is most likely explained by the distribution of the net household income in the city district.

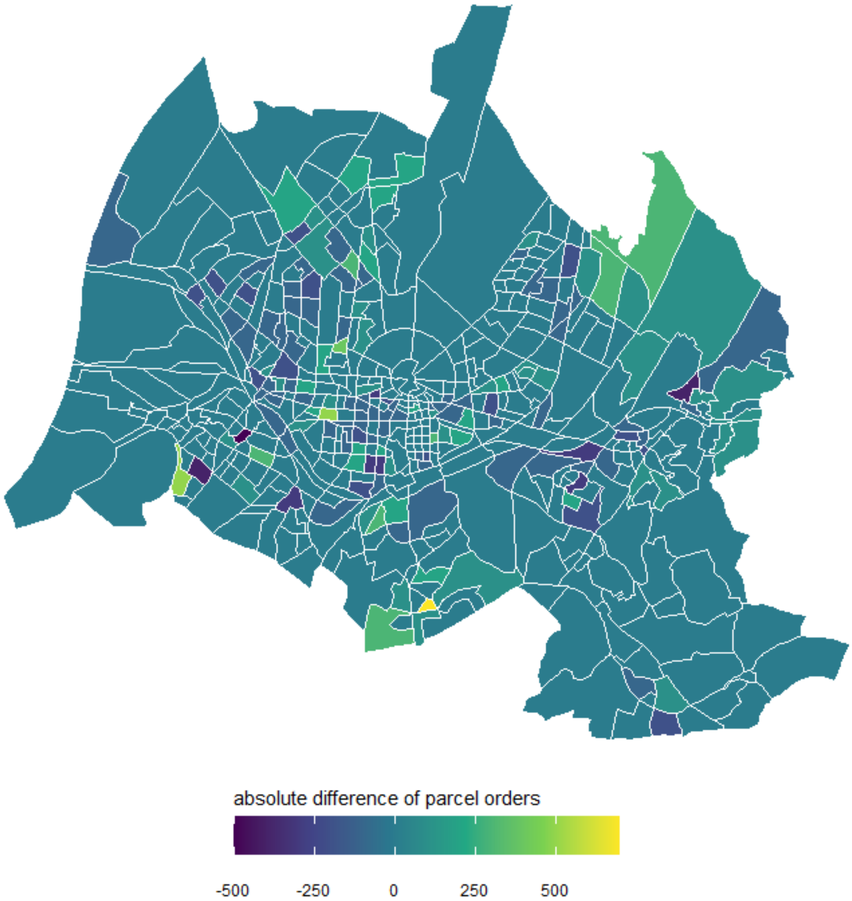

Figure 4: Absolute difference of parcel orders and deliveries between the two scenarios. Positive values represent an increase of deliveries in the Covid-19 scenario.

Our results show that there have been shifts in both socio-demographic characteristics of online shoppers and spatial distribution of parcel delivery demand induced by the Covid-19 pandemic. Results of the pre-pandemic scenario are consistent with studies on socio-demographic influence on consumers' e-commerce activity. Literature shows that prior to the pandemic, income has had a positive effect on online shopping behaviour [18, 19]. The results of our scenario analysis based on data collected during the pandemic show that the pandemic has somewhat shifted this interaction towards lower income groups. Considering the influence of e-commerce on consumption equality, previous research has shown that e-commerce can reduce consumption inequality [20]. Our results indicate that this effect has been positively influenced by the pandemic as people with a lower income have started or increased e-commerce activity. The scenario simulation based on the pandemic related data shows that not only the influence of income has shifted but also the effects of age on e-commerce activity has changed due to the pandemic. While the pre-pandemic scenario is consistent with previous literature suggesting that age has a negative influence on e-commerce [19], our results indicate that with the pandemic, also people aged 65 and older started or increased their use of e-commerce. The presented shift in socio-demographic characteristics is especially interesting considering that previous findings have highlighted that the influence of these factors on e-commerce activity cannot be changed through policy measures [19]. These findings were contradicted in times of the Covid-19 pandemic and we could observe that severe policy measures can have an effect on socio-demographic profiles of online shoppers. However, these measures were unprecedented and will not be imposed under regular circumstances. Nevertheless, the temporary closings of retails shops and the increased risk of infection during shopping trips lead a lot of people to switch shopping channels even if they had not (frequently) shopped online before.

While the previously discussed results could simply be studied through analysis of the survey data alone, the application of our model allows us to assess the results on a spatial level as well. The need to do so has been highlighted in previous studies, most recently Cheng et al. [21] analysed variables influencing the spatial distribution of parcel delivery demand. Among other variables, household characteristics play an important role for the correct prediction of spatial distribution of delivery trips. Taken together with the results of the scenario simulations of our study, our findings suggest that with the shift in socio-demographic profiles also came a change in spatial distribution of parcel delivery demand.

Many studies have highlighted the impact of accessibility measures on e-commerce activity and parcel demand [21, 22, 23, 24, 25, 26]. Due to the fact that the accessibility to in-store shopping was reduced rather by policy measures to decrease the spread of the virus than geographical or transport related factors, we did not account for accessibility in our study. However, as data becomes available from times with fewer or any pandemic related policy measures, we will update the model accordingly in future work. Another limitation of our study is the restriction of online shopping of durable goods. Online grocery shopping has accelerated during as a result of the pandemic [4]. Because of the different mechanisms of delivering durable vs. non-durable goods, simulating online grocery shopping behaviour and deliveries not only requires additional data but also an extension of the modelling framework. This extension will be part of future versions of *logiTopp*.

4 Conclusion

This study examines the effect of behavioural changes in online shopping induced and parcel delivery demand induced by the Covid-19 pandemic.

The scenario-based analysis shows an increase in parcel delivery demand changes consistent with surveys. The results of this study shows that the increase in demand can be traced back to people shopping online at higher frequencies and more people shopping online. There are two overarching implications of our findings: First, the extension of user groups of e-commerce by older people and those with a smaller income could lead to an acceleration of increase in e-commerce demand and that projected numbers will be reached faster than anticipated. And second, considering that the model area is a relatively small city, these results are disconcerting for larger cities and especially so for mega-cities. In population-dense areas, public space is scarce and the involvement of multiple providers delivering parcels uncoordinated in regards to their competition can lead to redundant delivery trips. Future research should thus focus on possible solutions to mitigate these problems, e.g. white-label deliveries in certain areas. The presented model framework and simulated scenarios help to assess future e-commerce demand and possible solutions to mitigate the problems caused by delivery traffic.

These findings are of interest to transport planners and delivery service providers as they highlight the importance of recognising that the Covid-19 pandemic not only induced a shift in socio-demographic profiles of online shoppers but that this shift also entails a change in the spatial distribution of parcel deliveries.

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