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With data from automated counting stations and controlling for weather and calendar effects, we estimate the isolated impacts of the "first wave" of Covid-19 pandemic and subsequent government intervention (contact restrictions and closures of public spaces) on walking and cycling in 10 German cities. Pedestrian traffic in pedestrian zones decreases with higher local incidence values, and with stricter government intervention. There are ambiguous effects for cycling, which decreases in cities with a higher modal share of cycling, and increases in others. Moreover, we find impact heterogeneity with respect to different weekdays and hours of the day, both for cycling and walking. Additionally, we use data on overall mobility changes, which were derived from mobile phone data, in order to estimate the modal share changes of cycling. In almost all cities, the modal share of cycling increases during the pandemic, with higher increases in non-bicycle cities and during stronger lockdown interventions.

Keywords: Covid-19 pandemic, before and during Covid-19 pandemic, active mobility, pedestrian, cycling, modal share.
JEL: R40, Q54.

Declarations of interest: none.

I. Introduction

The Covid-19 pandemic affects almost every aspect of everyday life, thus also changing general travel behavior. To begin with, the Covid-19 pandemic impacts on the overall need to travel. Due to the increase in working from home, contact restrictions, business and school closures, restrictions on leisure activities, or the rise in short-term work and unemployment, overall mobility decreases (e.g. Ehlert and Wedemeier, 2022; Schlosser et al., 2020). If one still has to travel, the transport mode decision is now influenced by the new challenges posed by the pandemic. The risk of infection impacts on personal security when traveling, with varying risk levels for different travel alternatives. While contact with other people is relatively high in public transport systems, the risk of infections is relatively low when driving alone in one's own car, walking or riding a bicycle (Zafri et al., 2022).

In this paper we focus on active mobility, that is, walking and cycling, and how these two transport modes were affected by the first wave of the Covid-19 pandemic in ten German cities. Our research goal is to estimate the isolated

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impact of the Covid-19 pandemic and subsequent government interventions. We focus on heterogenous effects between cities, times of the day and the severity of the interventions. The regression analysis with control variables such as weather and calender effects, as well as various types of fixed effects, is based on automated counting stations for pedestrians and bicycles. Furthermore, we evaluate the change in the modal share of cycling by combining the changes in bicycle ridership with overall mobility changes that are derived from mobile phone data.

On March 11, 2020, the World Health Organization (WHO) declared the spread of Covid-19 to be a pandemic. Since then, media outlets have tried to compare mobility behavior *before* the pandemic to that *during* the pandemic, and to draw conclusions based on these comparisons. Such comparisons are intuitive and can provide an initial indication as to how the pandemic could affect mobility, but they are neither suitable nor sufficiently accurate for deriving policy implications. While there are some studies on the impact of the Covid-19 pandemic on overall mobility (e.g. Borkowski et al., 2021) or public transport usage (e.g. Gkiotsalitis and Cats, 2020), there is less academic research on the impact of Covid-19 on active mobility. For New York City, Teixeira and Lopes (2020) find that subway ridership dropped by 90 %, whereas the usage of bicycle sharing systems dropped by only 71 %. Moreover, they find evidence of modal shifts from the subway system to the bikeshare system. Bucsky (2020) analyzes changes in various transport modes for Budapest and roughly approximates modal share changes. Moreover, a series of papers analyzes the impact of Covid-19 in Australia during different phases of the pandemic (Beck and Hensher, 2020a,b).[1] The aforementioned studies compare active mobility before the pandemic to active mobility during the pandemic, without controlling for weather or calendar effects. But in order to calculate the actual impact of the Covid-19 pandemic on mobility behavior, it is necessary to control for these external factors that simultaneously impact on mobility. There are various papers which analyze the impact of weather on walking and cycling in general (e.g. Aultman-Hall et al., 2009; Böcker et al., 2016; Ermagun et al., 2018; Miranda-Moreno and Nosal, 2011). Additionally, calendar events like public holidays, school holidays, and semester breaks have been shown to influence active travel (e.g. Ermagun et al., 2018; Wessel, 2020). Not controlling for these external factors could thus lead to distorted estimates.

Our specific contribution to the literature is to fill this research gap. First, we use hourly and automated data from over 125 counting stations in ten German cities. All pedestrian counting stations are located in pedestrian zones[2], and most bicycle counting stations are located at central points across the city. In combination with the control variables for weather and calendar effects, this allows us to determine the isolated impact of the first wave of the pandemic from March to July 2020. Second, the recent work of Zhang and Fricker (2021) has shown isolated impacts with weather control variables and daily data in a Bayesian structural time series model including a Difference-in-Difference framework among US cities. Our paper aims to answer open questions using hourly data and several government interventions, both for cycling and walking. We estimate the reaction to the pandemic situation when no government interventions were in effect, when either business/school closures or contact restrictions were active, or when both

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[1] For a more detailed overview, however, we refer to Buehler and Pucher (2021).
[2] Pedestrian zones are areas that are located in the city center and reserved for pedestrian-only use. Most or all automobile traffic is prohibited. The counted pedestrians thus reflect mostly shopping and commuting patterns, but cannot measure walking in nature.

business/school closures and contact restrictions were in effect. Additionally, we study the effect for different daytimes and weekdays.

Since the literature shows that there are statistically significant regional differences in attitudes towards cycling in general (e.g. Liu et al., 2014; Santos et al., 2013), it is reasonable to assume heterogenous reactions to the Covid-19 pandemic among cities. Research in Australia (Beck and Hensher, 2020b) and the Netherlands (de Haas et al., 2020) suggests an increase in cycling during the pandemic in countries with a low modal share of cycling, and a decrease in those with a high modal share. We focus on the city level and the difference in pre-pandemic modal share of cycling between the cities as well as the share of college students as a possible explanation for heterogeneous reactions during Covid-19. Last but not least, we combine the estimated changes in bicycle ridership with the changes in overall mobility that are derived from mobile phone data (Schlosser et al., 2020). Based on the initial modal share, we can derive percentage changes in the modal share of cycling for each city of the sample.

The remainder of this paper is structured as follows. The data and methods are outlined in Section II. In Section III, we analyze changes in overall mobility. Descriptive statistics and regression results for pedestrians in pedestrian zones and cyclists are presented in Sections IV and V. In Section VI, we calculate changes in the modal share of cycling. Section VII concludes.

II. Data & Methods

A. Cities of the Sample

An overview of the considered cities, the number of pedestrian and bicycle counting stations, as well as various city-specific information, can be found in Table 1. The cities of our sample are chosen according to several dimensions of their pre-pandemic heterogeneity. The sample includes larger and medium sized German cities, with populations between roughly 3.7 million (Berlin) and 160,000 (Heidelberg). Additionally, they differ in their modal share of cycling. Muenster, Heidelberg and Freiburg have a relatively high modal share of cycling and are often considered as "bicycle cities" in Germany (e.g. ADFC Bicycle Climate Index, 2019; Goldmann and Wessel, 2020). The opposite is true of cities like Berlin or Essen. Another dimension is the availability of public transport options such as subway or tram systems. Moreover, the cities are located in five different German states, thereby providing heterogeneity with respect to the timing of government interventions aimed at restricting the spread of the Covid-19 pandemic.

Table 1—: Cities of the Sample

City	Counters		Population	Modal Share			Bicycle City Rankings		Public Transport			Student Share
	Pedestrian	Bicycle		Walking	Bicycle	Public Transport	ADFC (2019)[2]	Weather (2020)[3]	Subway	S-Train	Tram	
Augsburg	1	2	300,000	31%	19%	16%	5	8	No	No	Yes	8.7 %
Berlin	3	23	3,660,000	30%	18%	27%	10	5	Yes	Yes	Yes	5.5 %
Bonn	3	9	330,000	28%	15%	17%	7	7	Yes	Yes	Yes	11.7 %
Duesseldorf	8	13	640,000	29%	12%	19%	8	9	Yes	Yes	Yes	9.4 %
Essen	1	2	590,000	19%	7%	19%	9	4	Yes	No	Yes	5.7 %
Freiburg	2	4	230,000	27%	23%	17%	2	3	No	No	Yes	13.7 %
Hanover	3	13	530,000	27%	19%	20%	4	6	Yes	Yes	Yes	9.5 %
Heidelberg	1	18	160,000	26%	26%	13%	3	2	No	No	Yes	22.7 %
Munich	2	6	1,490,000	24%	18%	24%	6	10	Yes	Yes	Yes	8.8 %
Muenster	2	9	310,000	22%	39%	10%	1	1	No	No	No	19.7 %

[2] Based on the overall grades of the ADFC Bicycle Climate Index (2019). Only the cities of our sample are considered for this ranking. The index is a non-representative survey with the aim of comparatively recording cycling conditions in cities and municipalities. The survey is based on subjective assessments of aspects that are important for cycling. The answers can be given on a scale from 1 to 6, comparable to the school grading system. Finally, a grade is calculated from all answers. In 2018 about 150.000 participants joined, 683 cities with a minimum of 50 - 100 responses have been evaluated and graded. More information is available at https://t1p.de/5oeso.
[3] Based on the weather elasticities from Goldmann and Wessel (2020). Only the cities of our sample are considered for this ranking.

B.   Counting Stations

Counting stations for both walking and cycling provide automated and hourly data. For each city, at least one pedestrian and bicycle counting station is available. The pedestrian counting stations are installed and provided by Hystreet, a mobility start-up that focuses on passenger traffic flows in pedestrian zones of German cities. Thus, walking in nature is not captured by these counting stations. Counting is done by permanently installed laser scanners, which can achieve a counting accuracy of 99 percent at a flow rate of up to 500 people per minute. Similar data has recently been used in transport research (e.g. Goecke and Rusche, 2020; IFW Kiel, 2021). For our analysis, we use data from 26 stations in 10 German cities.[3]

Bicycle counting stations are installed by EcoCounter and measure the number of cyclists per hour with below-surface induction loops. The measuring accuracy[4] of the considered counting stations is above 95 %, and similar data are frequently used in related studies on bicycle ridership (e.g. Kraus and Koch, 2021; Miranda-Moreno and Nosal, 2011). For our analysis, we use data from 99 bicycle counting stations.

The exact location of each considered counting station can be found in Figure A1 in Appendix A.A1. For pedestrians, all stations are placed in pedestrian zones in the city centre. For bicycles, most counting stations are installed at bicycle lanes with higher bicycle traffic, e.g. at important connecting routes. To increase comparability between cities, we classify bicycle counters as utilitarian, recreational, and mixed, according to the classification procedure outlined in Wessel (2020). Based on pre-pandemic cycling levels, 83 of our counting stations can be classified as utilitarian, 4 as recreational, and 17 as mixed. A preliminary analysis of bicycle ridership during the pandemic shows that traffic at utilitarian and mixed counting stations behaves rather similarly. Due to the very limited number of recreational counting stations, and the fact that bicycle traffic at these counting stations varies substantially from traffic at other stations, we exclude them from our analysis. By focussing only on utilitarian and mixed stations, we thus ensure a sufficient degree of comparability between cities.

Since there are very few counts of pedestrians and cyclist during the night hours, we only use data from 5:00 in the morning to 22:59 in the evening.

C.   Covid-19 Data and Government Intervention

The observation period of our study is from January 1, 2019, to June 30, 2020. According to the WHO, the spread of Covid-19 reached the state of a pandemic on March 11, 2020. We thus refer to the days between March 12, 2020, and June 30, 2020, as days of pandemic. The considered observation period is chosen so that it comprises the so-called "first wave" in Germany, which the Robert Koch-Institut (RKI) classifies as ending around June 2020 (Schilling et al., 2021). The main reasons for focussing on this wave of the pandemic are its clearly defined duration and the government interventions in effect. Consequently, the presented results hereinafter are valid for the first wave of the Covid-19 pandemic in Germany.

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[3] Three of the 26 considered pedestrian counting stations were only installed in the first months of 2019 and therefore do not provide data for the entire period. Each counting station provided data for at least 412 consecutive days.

[4] The bicycle counting stations measure the electromagnetic profile of passing vehicles. As the bicycle profile is quite unique, scooters, mopeds or cars on shared bike lanes are not counted as bicycles.

Traffic responses during subsequent waves, however, could differ from our findings, as, for example, the dynamics and circumstances of the second wave already differed from those of the first.

The Covid-19 data are taken from RKI. This dataset contains daily information on newly reported Covid-19 infections within each county (NUTS3 region). The region-specific incidence values are calculated as the average of reported new Covid-19 infections over the previous seven days, divided by the region's population. They are presented in new cases per 100,000 inhabitants. The population numbers of the counties are obtained from the Federal Statistical Office.

In addition to Covid-19 case numbers, we also control for government interventions that were introduced to reduce the mobility of the population, thereby helping to contain the spread of the virus. Non-essential businesses and schools were closed. Moreover, there were also restrictions on personal contacts to reduce the risk of infection in private encounters. This was implemented by restricting the number of people that were allowed to meet, or by curfews restricting the times of day when people were allowed to meet.

To estimate the impact of such government intervention on active mobility, we collect data on the timing of non-essential business closures, school closures, curfews, and restrictions on the number of people allowed to meet. One problem that arises is the correlation in timing of these interventions. Especially school and non-essential business closures were in effect for very similar dates, in some cities even for the exact same dates. Thus, disentangling the effects of specific interventions can become problematic.

To mitigate such problems, we do not look separately at each intervention, but rather at the degree to which life was affected by the pandemic and subsequent government interventions. We therefore define two broader types of government interventions as follows. The first intervention type, i.e. closures of highly-frequented public spaces, was in effect if the government prohibited non-essential businesses from opening, or if schools were closed. The second intervention type, i.e. contact restrictions, was in effect if there were either curfew restrictions, or if meetings with more than one person from another household were not allowed. An overview of the periods during which these two types of interventions were in effect can be found in Figure A2 in Appendix A.A2. Brauner et al. (2021) show that these two types of interventions had the largest impacts on Covid-19 transmissions. Other interventions, such as compulsory face mask policies, appeared not to have affected community mobility in public spaces in Germany (Kovacs et al., 2020). In line with these studies, we therefore focus our analysis on contact restrictions and closures of public spaces.

Based on these definitions, we then create three separate dummy variables to capture the severity of government intervention. The variable *pandemic_no_intervention_type* refers to days during the Covid-19 pandemic for which no type of government intervention was in effect. The variable *pandemic_one_intervention_type* refers to days during the Covid-19 pandemic for which either closures of public spaces or contact restrictions were in effect. Finally, the variable *pandemic_two_intervention_types* refers to days during the pandemic for which closures of public spaces were in effect and contacts restricted. The reference category is then the period before the pandemic. During the pandemic, about half of the observations are without active government interventions, one quarter with one intervention type, and one quarter with two.

D. *Mobility Data, Weather Data and Calendar Events*

The change in overall mobility in German NUTS3 regions is based on mobile phone data from the network provider Telefonica, which was processed and anonymised by Teralytics and made available by Schlosser et al. (2020). Movements are recorded from mobile phone logs to different cell towers.[5] These data have recently been used as an approximation for mobility in transport research (e.g. Ehlert and Wedemeier, 2022; Jarass et al., 2022). For our purposes, we use the data on mobility changes from all dates between February 1, 2020, when data provision starts, and June 30, 2020. A mobility change in NUTS3 region i is then defined as

$$(1) \qquad\qquad \frac{mobility_{i,t}}{mobility_{i,t^*}} - 1,$$

where $mobility_{i,t}$ is the number of trips in region i within timeframe t, and t^* is a comparable timeframe with normal mobility. For the provided data, the comparable timeframe always refers to the average corresponding weekday of the corresponding month in 2019 (pre-Covid-19). That is, the mobility on Saturday, February 1, 2020, is compared to the average mobility on Saturdays in February 2019.

To account for systematic changes in weather conditions between 2019 and 2020, we use information on air temperature, precipitation, and wind speed. For precipitation, two separate dummy variables are created, one for light rain ($0\,\mathrm{mm}$ < precipitation < $2.5\,\mathrm{mm}$), and one for stronger rain (precipitation $\geq 2.5\,\mathrm{mm}$). The weather data are obtained from the nearest weather stations to each city and are provided by the Deutscher Wetterdienst (DWD). Additional dummy variables account for school holidays, public holidays and university semesters.

E. *Methods*

ESTIMATING CHANGES IN WALKING AND CYCLING

Our identification strategy is twofold. To identify regional impacts of different lockdown situations on pedestrian and cycling levels, we estimate negative binomial regression models with the respective count data as the dependent variable. Based on Winkelmann (2008), this model type with Poisson distribution is regularily used for count data, especially to control for overdispersion. Independent variables are incidence values and the three intervention-type variables. To identify the impacts of these variables, we exploit the regional variation in timing of the underlying government intervention, which were implemented at the state-level. This also implies that a single city had no unilateral power to decide on the timing of government interventions, and had to follow the decisions that were made the state level.

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[5] The methodology for movement detection works as follows: A trip starts whenever a mobile device leaves the current cell tower area A. The device might then pass through one or multiple other cell towers, until it becomes stationary again in cell tower area B. "Stationary" means that no further movement is recorded for approximately 15 minutes. The start- and end-towers A and B can be the same, such that self-loops are also recorded. All movements are then aggregated spatially at the level of NUTS3 regions (Schlosser et al., 2020). Mobility changes are defined as changes in movements. Errors like fluctuations in signal strength or differencens in the size of cell tower areas are reasons for possible distortions. For differentiated local market shares of the provider, Teralytics use an algorithm to extrapolate for the total German population.

We control for weather conditions and calendar events. In particular, we include variables for air temperature (linear and squared), precipitation (low and high), wind speed, public holiday, school holidays and semester breaks. By using counting station fixed-effects and hour×weekday fixed-effects, we control for idiosyncrasies of different counter locations as well as time effects. With this setting, we can estimate the isolated impact of different intervention types both for cycling and walking.

Estimating Changes in the Modal Share of Cycling

To calculate city-specific percentage point changes in the modal share of cycling, we combine changes in cycling, changes in overall mobility, and the pre-pandemic modal share of cycling. A detailed mathematical description of the procedure for calculating the changes in the modal share of cycling can be found in Appendix A.A3.

These three different types of information are obtained as follows. For changes in cycling, we estimate the isolated impacts of the pandemic and subsequent government intervention according to the methods outlined in Section II.E.

For changes in overall mobility, we similarly estimate isolated impacts based on the mobility data from mobile phones that was introduced in Section II.D. The data from mobile phone providers, which is made available by Schlosser et al. (2020), offers a good approximation of mobility, but might be distorted by differences in the occurrence of calendar events, or in weather conditions between the timeframe t and the comparable timeframe t^* in Equation 1. Therefore, we control for changes in official holidays, school holidays, semester breaks, temperature, windspeed, and precipitation, by calculating changes in these mobility determinants in a manner comparable with mobility changes[6]:

$$(2) \qquad \text{control\_variable\_change} = \text{control\_variable}_{i,t} - \text{control\_variable}_{i,t^*}.$$

We then regress the mobility change in a linear regression model on the control variables that were transformed according to Equation 2, as well as the three intervention-type variables for each city. The undistorted changes in overall mobility are outlined in Section III.

The pre-pandemic modal share of cycling for each city is obtained from the special report Mobilität in Deutschland by the Ministry of Transport (Nobis and Kuhnimhof, 2018) and other sources. They are printed in Table 1.

III. Changes in Overall Mobility

The point estimates and 95 % confidence intervals for the undistorted impacts of the Covid-19 pandemic on overall mobility in each city are illustrated in Figure 1.[7] The results show that mobility decreased sharply during the pandemic. The mobility decrease is stronger for more severe interventions in each city. For the days of the pandemic on which no government intervention types were in effect, mobility changes lie between −12.0 % in Essen and −24.1 % in Heidelberg. If either closures or contact restrictions were in effect (*one_intervention_type*), mobility drops between −26.3 % in Essen and −39.4 % in Heidelberg. The biggest

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[6] In contrast to the mobility change, however, we do not calculate percentage changes for our control variables, in order to avoid division by zero.

[7] Detailled Regression results are presented in Table A2 in Appendix A.A6.
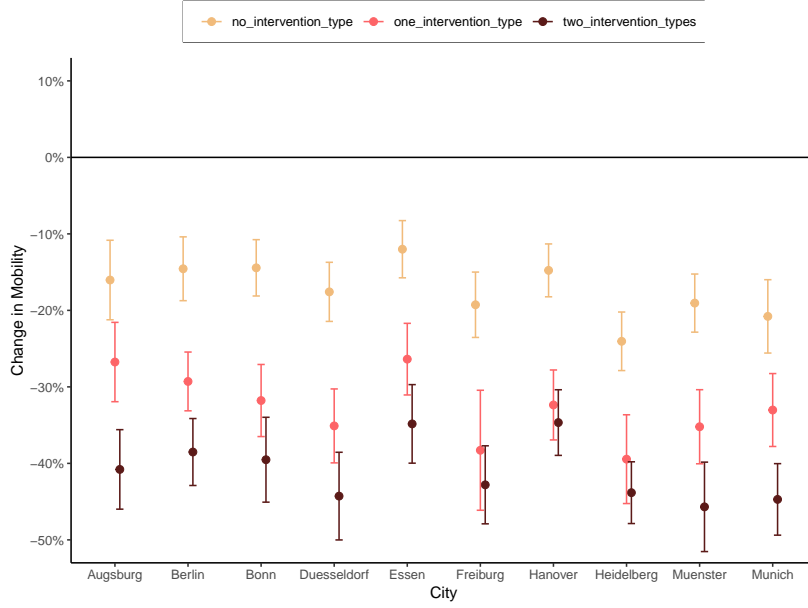
Figure 1. : City-specific Point Estimates and 95 % CI of Overall Mobility Changes for Different Intervention-Type Variables

decrease in mobility during the pandemic can be found for the strictest interventions. The estimates of the *two_intervention_types* variable (closures and contact restrictions at the same time) range between -34.6% in Hanover and -45.7% in Muenster. In conclusion, the results underline that our three created intervention-type variables indeed reflect the intensity of the pandemic situation and its impact on mobility in an adequate way. Hence, they are suited for the following analysis of pedestrian and cycling counts.

IV.   Analysis of Changes in Pedestrian Traffic in Pedestrian Zones

A.   Descriptive Analysis

To get an overview about changes in pedestrian counts during the pandemic, we can use a descriptive analysis. For that we display the average number of counted pedestrian per hour and station, separated over the first 26 weeks of 2019 and 2020 in Figure 2. The weekly pedestrian counts fluctuate quite visibly, which could be attributed to different weather conditions or calendar events, for example an increase in shopping trips during Easter vacations (Week 16 of 2019).

The dashed line between Weeks 11 and 12 represents the beginning of the Covid-19 pandemic according to the WHO, which was followed by stricter government interventions, including non-essential business and school closures in Week 12. There is a visible decline in pedestrian counts during Weeks 10 and 18. Hence, pedestrian levels decreased even two weeks before the German government officially ordered closures. In Week 13, pedestrian counts declined by 85.5%, compared to the same week in 2019. Between Weeks 17 and 22, pedestrian counts started to increase again, which can be attributed to a re-opening of non-essential businesses that began in Week 16 in most German states. Nevertheless, pedestrian counts did not reach the numbers of the previous year until the end of the
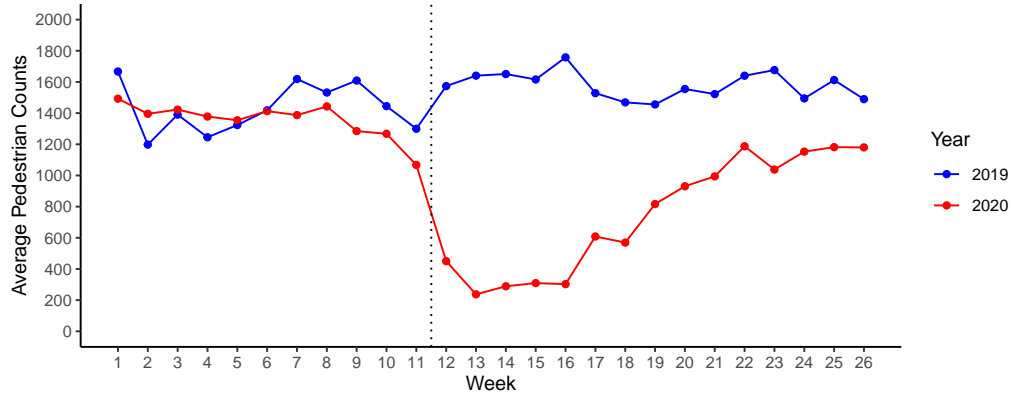
Figure 2. : Average Pedestrian Counts per Hour in 2019 and 2020

observation period.

City-specific average changes during the first wave of the pandemic from March 12, 2020, to June 30, 2020 compared to the same period in 2019 can be found in Table 2. There are smaller differences between the cities in the size of pedestrian decrease. Nevertheless, all changes are negative and show roughly a halving of pedestrian volumes in each city.

Table 2—: City-Specific Changes in Pedestrian Traffic

	Augsburg	Berlin	Bonn	Duesseldorf	Essen	Freiburg	Hanover	Heidelberg	Munich	Muenster
Change Pedestrians (in %)	−40.6	−59.1	−44.6	−49.7	−45.9	−47.0	−50.6	−51.2	−64.2	−44.9

The displayed changes in traffic volumes are calculated by comparing city-specific traffic volumes between 12.03.2020 and 30.06.2020, to traffic volumes between 12.03.2019 and 30.06.2019.

As the pedestrian counting stations are installed in pedestrian zones, they are determined by the weekdays and opening hours of the stores. Figure 3 displays the average pedestrian counts per hour, broken down by weekdays, Saturdays and Sundays. The red line represents average counts during the first wave of the pandemic in 2020, and the blue line represents average counts during the same period in 2019. In general, it can be seen that the fewest pedestrians are counted on Sundays when most shops are closed, visibly more are counted on weekdays, and most on Saturdays. On weekdays and Saturdays, most pedestrians are counted during the regular opening times of the stores, which usually open between 8:00 and 10:00, and close between 18:00 and 20:00.

There is a clearly discernible impact of the Covid-19 pandemic on pedestrian counts during opening hours. On weekdays, the number of pedestrians per hour during the period of the Covid-19 pandemic is 46.9% lower than in the same period of the previous year. On Saturdays, the reduction is about 53.7% and on Sundays, there are about 56% fewer pedestrians. Interestingly, although it is not directly visible in the graph, the late evening hours (when stores are closed) from 20:00 to 22:59 are most affected by the pandemic with a reduction of over 60%.
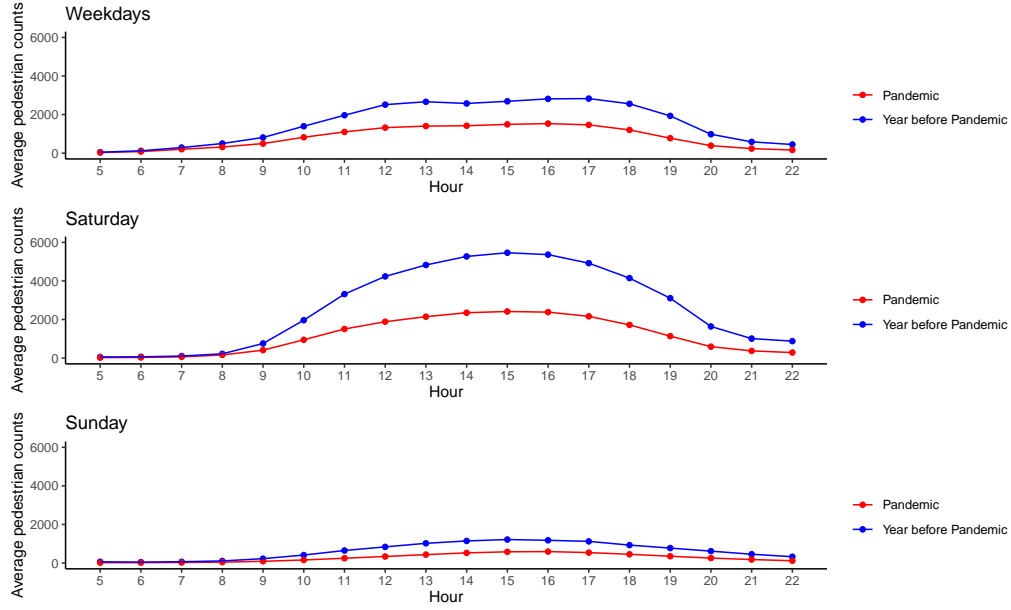
Figure 3. : Average Pedestrian Counts per Hour Before and During Pandemic

B.   Regression Analysis: Impacts of the Pandemic and Government Intervention

As outlined in the introduction, a purely descriptive analysis cannot represent isolated pandemic effects because, for example, biases due to weather and calendar effects can occur. Therefore we use the described negative binomial regression models with weather and calender effects as control variables, counting station fixed and hour×weekday fixed-effects. As incidence values are correlated with stricter government intervention, we include both the incidence value and our three dummy variables on the severity of government intervention in order to mitigate concerns from potential omitted variable bias. The results for the impact of the pandemic on pedestrian traffic in pedestrian zones are presented in Table 3. In Model (1), a higher *incidence_value*, which is broadcast to the public by various media outlets, generally implies a higher risk of infection and thus reduces pedestrian levels. If one more person per 100,000 inhabitants was infected within in the last 7 days, about 0.73 % fewer pedestrians are counted.[8]

The coefficients for the dummy variables show that walking volumes decreased by 30.7 % during the first wave of the pandemic for which no governmental intervention type were in effect. This underlines that being in a pandemic itself, and the associated fear of infection, already reduces walking in heavily frequented pedestrian zones – even in the absence of government restrictions.

Stricter government interventions, however, reduce the number of pedestrians even further. If either closures or contact restrictions were in effect, pedestrian volumes decreased by roughly 56%, and if both intervention types were in effect, even by 65%. This implies that government interventions were in fact effective in reducing pedestrian levels in pedestrian zones. Since just a few essential stores

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[8]   It should be noted that incidence values during the first wave of the Covid-19 pandemic were relatively low compared to values in the second or third wave. In our sample, the highest incidence value was registered on April 3rd in Freiburg, with 119.84.

Table 3—: Walking Regressions

Dependent Variable:	log(pedestrian_counts)			
Subsample:	All	Weekdays	Saturday	Sunday
Model:	(1)	(2)	(3)	(4)
pandemic_no_intervention_type	-0.3673***	-0.3241***	-0.3871***	-0.5886***
	(0.0321)	(0.0306)	(0.0367)	(0.0325)
pandemic_one_intervention_type	-0.8156***	-0.7315***	-1.021***	-1.041***
	(0.0485)	(0.0365)	(0.0528)	(0.0656)
pandemic_two_intervention_types	-1.048***	-1.055***	-1.288***	-1.065***
	(0.0774)	(0.0758)	(0.1334)	(0.0508)
incidence_value	-0.0073***	-0.0065***	-0.0104***	-0.0066***
	(0.0012)	(0.0012)	(0.0021)	(0.0017)
public_holidays	-0.8298***	-0.9028***		-0.1000*
	(0.0857)	(0.0617)		(0.0574)
school_holidays	0.0179	0.0426***	-0.0751***	-0.0389
	(0.0159)	(0.0110)	(0.0112)	(0.0249)
semester	0.1113***	0.1141***	0.1075***	0.1320***
	(0.0160)	(0.0118)	(0.0211)	(0.0272)
temperature	19.20***	16.50***	4.208***	7.519***
	(4.152)	(2.610)	(1.609)	(2.063)
temperature^2	-21.42***	-14.08***	-8.164***	-19.90***
	(2.778)	(1.429)	(1.238)	(1.511)
light_rain	-0.2632***	-0.2439***	-0.2263***	-0.3780***
	(0.0204)	(0.0190)	(0.0215)	(0.0294)
strong_rain	-0.3790***	-0.3303***	-0.3692***	-0.5636***
	(0.0457)	(0.0336)	(0.0423)	(0.0570)
wind speed	-0.0127***	-0.0096***	-0.0167***	-0.0232***
	(0.0017)	(0.0013)	(0.0037)	(0.0040)
Counter-FE	Yes	Yes	Yes	Yes
Hour×Weekday-FE	Yes	Yes	Yes	Yes
Observations	234,472	167,664	33,420	33,388
Pseudo R^2	0.13450	0.13262	0.13874	0.14077
Overdispersion	4.6996	5.5009	4.6684	3.9999

Two-way (Counter & Hour×Weekday) standard-errors in parentheses.
Significance Levels: ***: 0.01, **: 0.05, *: 0.1.

for daily needs (e.g. supermarkets or bakeries) remained open, regular shopping behaviour or eating out in restaurants was no longer possible. These results hold, however, only for pedestrian levels in heavily frequented pedestrian zones, allowing no inference for more recreational types of walking.

In Section IV.A, we saw that the highest pedestrian levels can be found on Saturdays, followed by weekdays and Sundays. Therefore, we run regression model (1) again for separate subsamples of different types of days, resulting in regression models (2), (3), and (4). The results show that there are heterogeneous effect magnitudes across different types of days. In the absence of government intervention, the highest decrease in pedestrian traffic during the pandemic can be observed on Sundays (4). If government interventions are in effect, however, the highest decreases occur on Saturdays (3), with a reduction of 64.0 % in the case of *one_intervention_type*, and a reduction of 72.4 % with *two_intervention_types*. Since Saturdays are the busiest shopping days, this result is not surprising.

Moreover, all regression models underline that weather and calendar effects are important determinants of pedestrian levels, and should thus always be accounted for. In general, air temperature has a non-linear impact on pedestrian levels in pedestrian zones, implying that warmer temperatures increase pedestrian traffic until a certain point, after which on it is too hot and a further increase in temperature would actually decrease pedestrian levels. Rain and windspeed impact negatively on pedestrians. Moreover, *public_holidays* decrease pedestrians levels, which can be attributed to store closures. During the university *semester*, more counts are registered since there are more students in the city. The effect for *school_holidays* is ambiguous and not statistically significant, which could be explained by two opposing effects. On the one hand, people are more likely to be on vacation, and thus cannot walk through the pedestrian zones in their hometowns; on the other hand, people who are not on vacation are more likely to go shopping.

The results are rather similar for the various cities in the sample, which is why we refrain from conducting separate analyses for each city, as is subsequently done in the analysis of cycling levels.[9]

C.   Regression Analysis: Impact Heterogeneity Between Hours of the Day

The impact of the Covid-19 pandemic on pedestrian levels in pedestrian zones is neither constant throughout the day, nor for different days of the week. Therefore, we now run a negative binomial regression model with hour-specific dummy variables for the Covid-19 pandemic. Additionally, these hour-specific dummy variables are differentiated according to weekdays, Saturdays, and Sundays. Thus, the dummy variable *pandemic_Weekday_05* takes the value 1 for pedestrian counts between 5:00 and 5:59 on weekdays during the Covid-19 pandemic, and 0 otherwise. All in all, we include 18 hour-specific dummy variables for the hours from 5:00 to 22:59 on weekdays, as well as 18 hour-specific dummy variables for Saturdays, and also 18 for Sundays. Figure 4 plots the log-transformed 54 hourly effects and the 95 % confidence intervals for a regression model that features these dummy variables, as well as the usual control variables and fixed effects.[10].

We find that all estimates are negative, implying that pedestrian levels in the

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[9] The results for city-specific regressions are available upon request.

[10] The original point estimates and confidence intervals are transformed by $(e^{\hat{\beta}} - 1) * 100$ in order to obtain the actual percentage changes. Detailed regression results for the hour-specific regression are available upon request.
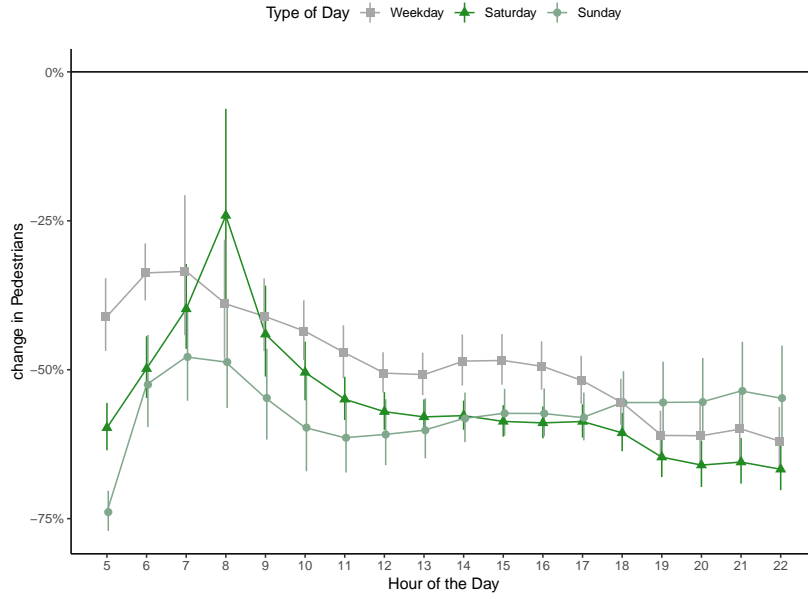
Figure 4. : Point Estimates of Hourly Covid-19 Pandemic Impact on Walking

pandemic decreased during each hour of the day, and for each type of day. For Saturdays and Sundays, we find that there are strong decreases between 5:00 and 5:59. This might be due to closed clubs and party locations during the pandemic, which results in almost no counts being registered during the pandemic. On Saturdays and Sundays, the smallest decrease can then be noticed from 7:00 to 8:59. One reason for this might be the relatively constant demand for bakery stores in the morning, which were allowed to open even during the strictest lockdown. Interestingly, a similar effect can be observed for two hours earlier on weekdays, which seems reasonable, as most people need to get up earlier on weekdays as opposed to weekend days. For all types of days, the reduction in pedestrian traffic is stronger in the subsequent afternoon and evening hours. This can be attributed to a reduction in contacts and leisure activities.

With respect to the different types of days, we can see that the reduction in pedestrian traffic is most pronounced on Saturdays, the main shopping day of the week. For weekdays and Sundays, however, the reductions are less pronounced.

V.   Analysis of Changes in Bicycle Ridership

A.   Descriptive Analysis

In Figure 5, the average hourly bicycle counts over all stations of the sample are displayed. There is a clear drop in overall bicycle counts during Weeks 12 to 14. As the first half of the year progresses, cycling counts increase again, but with great volatility. In some weeks, the 2020 counts exceed those of the previous year, whereas they are lower in other weeks. Thus, a visible decrease in cycling is only evident for the immediate weeks after the outbreak of the pandemic. After this, there is no clear effect.

On the other hand, there appear to be clear changes in bicycle ridership for certain times of the day, both for weekdays and weekends. Figure 6 presents
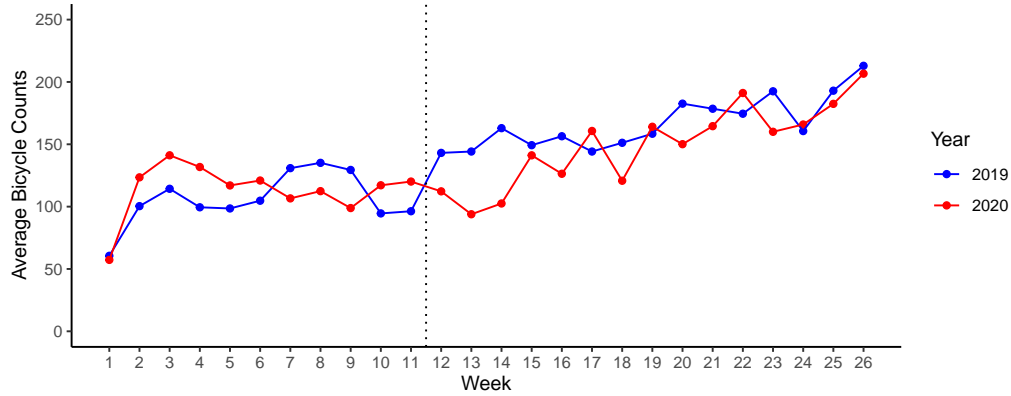
Figure 5. : Average Bicycle Counts per Hour in 2019 and 2020

the average hourly bicycle counts in the period before and during the Covid-19 pandemic. On Saturdays and Sundays, bicycle ridership is visibly higher during midday hours and especially in the early afternoon, indicating an increase in leisure trips on weekends. In the evening hours, bicycle ridership is reduced, which could be due to government interventions like curfews or the temporary closure of bars, restaurants, and cinemas. Hourly bicycle ridership during weekdays shows a different pattern. There is a clear reduction in bicycle traffic during the morning peak hours, as well as in the late afternoon and evening. The widespread use of working from home and the temporary closure of shops and leisure activities could potentially explain this development.
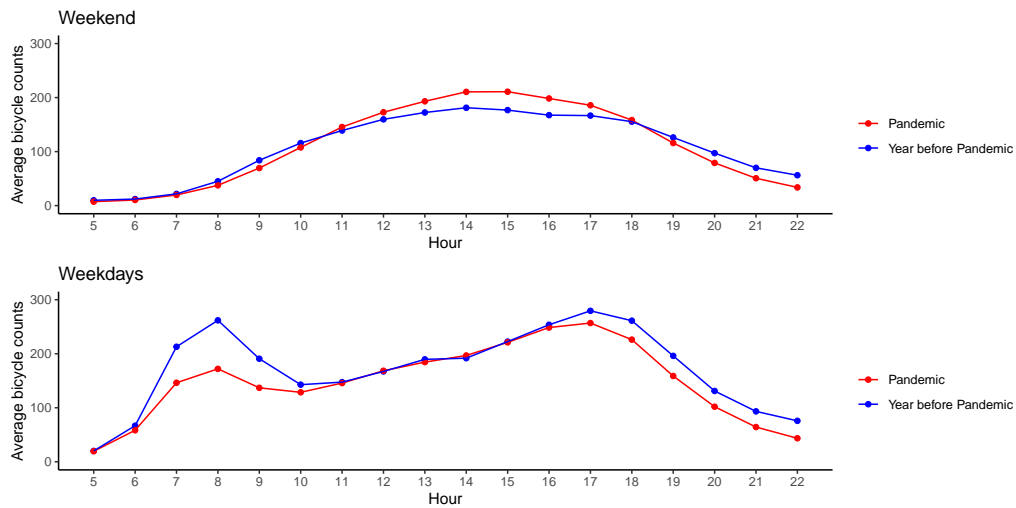

Figure 6. : Average Bicycle Counts per Hour Before and During Pandemic

While walking in pedestrian zones decreases in every city, the impact of the pandemic on bicycle ridership shows heterogenous changes between the cities of the sample. Table 4 outlines these changes. In bicycle-friendly cities with a higher modal share of cycling, such as Muenster, Heidelberg, or Freiburg, bicycle

ridership decreases during the pandemic, whereas it increases in other cities with a lower modal share of cycling and more public transport options, such as Essen, Duesseldorf, or Bonn. This impact heterogeneity on cycling levels across German cities will be analyzed further in the following sections.

Table 4—: City-Specific Changes in Bicycle Traffic

	Augsburg	Berlin	Bonn	Duesseldorf	Essen	Freiburg	Hanover	Heidelberg	Munich	Muenster
Change Cyclists (in %)	-8.4	2.7	17.1	26.6	50.6	-20.9	-3.0	-36.7	8.2	-31.3

The displayed changes in traffic volumes are calculated by comparing city-specific traffic volumes between 12.03.2020 and 30.06.2020, to traffic volumes between 12.03.2019 and 30.06.2019.

B.   Regression Analysis: Impacts of the Pandemic and Government Intervention

As outlined in the introduction, pre-pandemic attitudes towards cycling vary strongly across German cities (e.g. ADFC Bicycle Climate Index, 2019; Goldmann and Wessel, 2020). Additionally, we have seen heterogenous changes in bicycle ridership in the descriptive analysis. To analyse the isolated impact of different government intervention during the first wave on cycling, we run the same negative binomial regression model with control variables and fixed effects as we did for pedestrian counts. This model is run separately for each city in order to analyse heterogeneity between the cities of the sample. The regression results, i.e. the transformed point estimates of the three intervention-type variables and the corresponding 95 % confidence intervals, are then illustrated in Figure 7 to show city-specific percentage changes in bicycle ridership.[11]

We find evidence of the assumed heterogeneity between the ten considered cities. Cities such as Berlin, Bonn, and Duesseldorf have statistically significantly more bicycle traffic during the pandemic. The highest increases can be found when both intervention types were in effect, especially in Bonn with an increase in bicycle ridership of about 45 %.

In Muenster, Heidelberg, and Freiburg, the opposite effects can be found. For Muenster, bicycle ridership declined by 21.4 % on days in the pandemic when no government intervention type were in effect. The introduction of a government intervention reduced bicycle ridership even further, by roughly 39 %. For Heidelberg, we can also see a reduction in bicycle ridership, with the strongest effect for days with one government intervention type. In Freiburg, we find negative and significant effects on bicycle ridership for days during the pandemic both for the *one_intervention_type* and the *two_intervention_types* variable.

The regression results underline that cycling increases in some cities, and decreases in others. Comparing the changes in bicycle ridership with key figures from Table 1, we can see that cycling increases in cities with a relatively low modal share of cycling, and decreases in cities with a higher modal share.

In cities where the Covid-19 pandemic has led to more people using and discovering bicycles, in addition to the low pre-pandemic bicycle mode share, we find high population density, a relatively lower share of students, and larger public transport systems. Therefore, the bicycle can be used as a substitute for public transport in these cities, as public transport entails a lot of contact with other

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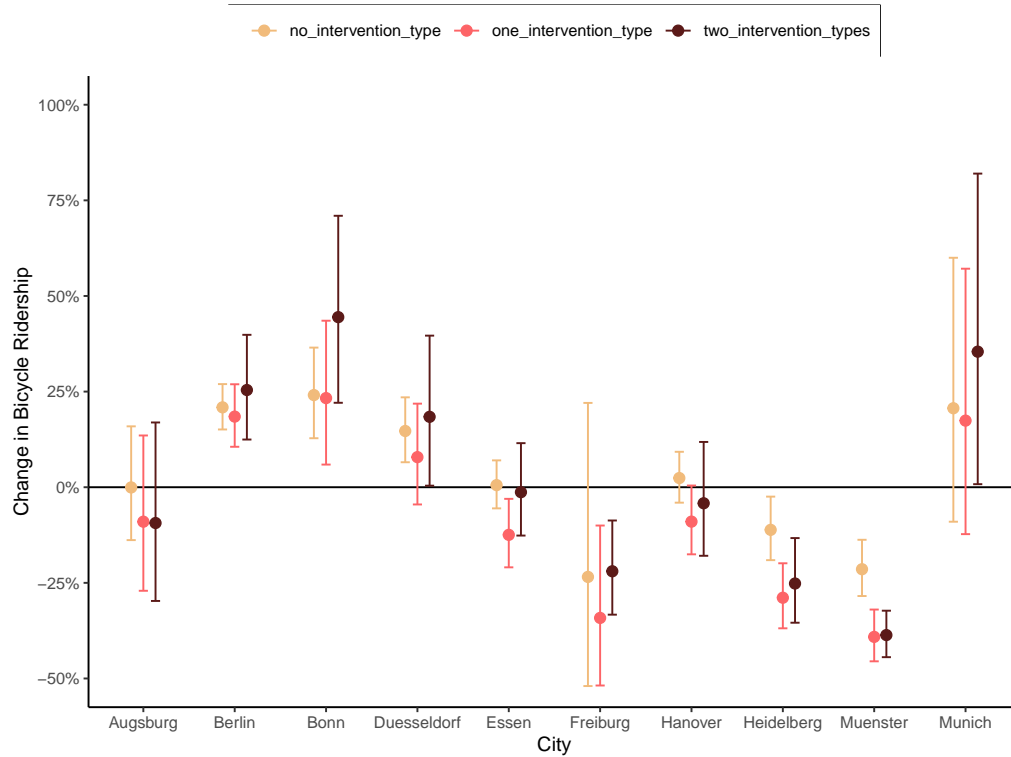[11] Detailed regression results are presented in Table A3 in Appendix A.A7.

Figure 7. : City-specific Point Estimates and 95 % CI of Cycling Changes for Different Intervention-Type Variables

people, and hence, a heightened risk of infection with Covid-19.[12] Furthermore, cities like Berlin and Duesseldorf have installed pop-up bike lanes in the first weeks of pandemic. Since the provision of good infrastructure has been generally identified to increase cycling (e.g. Pucher et al., 2010), Kraus and Koch (2021) find an increase of 11 % to 48 % in cities with new pop-up bike lanes during the pandemic compared to cities without these infrastructural changes. This additional effect needs to be kept in mind when analyzing the estimates for Berlin and Duesseldorf. Moreover, cycling could be used more and more for recreational activities, as, for example, gyms were closed and many team sports temporarily restricted.

The cities in which bicycle ridership decreases are also generally regarded as German "bicycle cities". In addition to the high pre-pandemic modal share of cycling, these cities have lower population densities, a high share of students and no subway system. Thus, it could be argued that there are fewer people switching from public transport to cycling in these cities. Moreover, many students in these university cities moved back in with their parents due to remote learning among others (Schwegler et al., 2021).

In general, these differences between cities could be attributed to the interplay of two opposing effects: (i) a general decrease in mobility which leads to a decrease in

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[12] Due to lack of public transport data we cannot directly estimate these switching effects, nevertheless a survey study of Anke et al. (2021) among 4,157 German public transport users verify a statistically significant change to cycling during the pandemic.

bicycle ridership, and (ii) potential shifts from public transport to cycling and/or increases in leisure cycling. For Berlin, Bonn, and Duesseldorf, the former effect appears to be weaker than the latter, while the converse applies to Muenster, Heidelberg, and Freiburg.

In Augsburg, Essen, and Munich, no statistically significant changes in bicycle ridership can be found during the pandemic, indicating that the two effects might have cancelled one another out. For Hanover, bicycle ridership only decreased during days when at least *one_government_intervention_type* was in effect, and did not change during other days in the pandemic. Although bicycle ridership remained relatively constant in these four cities, there might still be significant modal share changes caused by a decrease in overall mobility. This is analyzed further in Section VI.

C. Regression Analysis: Impact Heterogeneity Between Hours of the Day

Similar to pedestrian traffic, the impact of the Covid-19 pandemic on bicycle ridership is neither constant throughout the day nor for different weekdays. Therefore, we run a similar regression model as in Section IV.C, without the distinction between Saturdays and Sundays. Figure 8 plots the transformed hourly effects and confidence intervals for such a regression model.
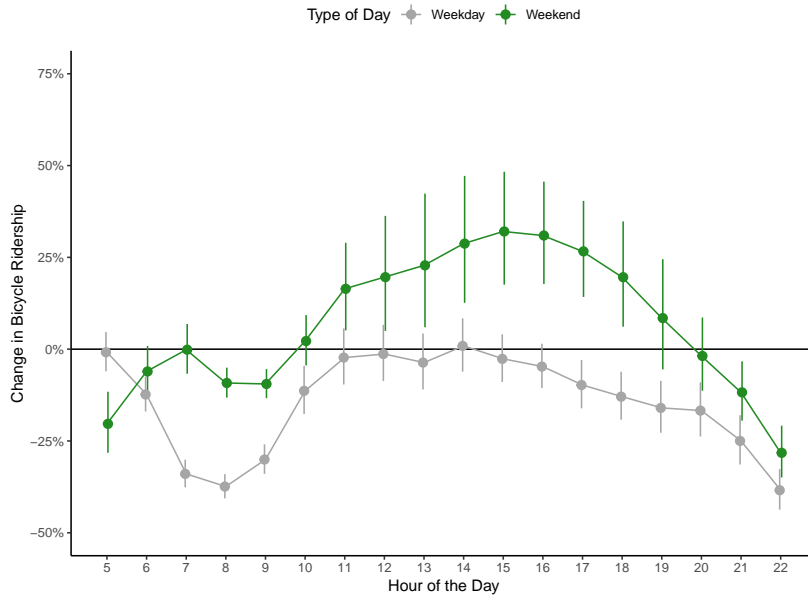

Figure 8. : Point Estimates of Hourly Covid-19 Pandemic Impact on Cycling

A closer look at the hourly traffic on weekends shows that there are substantial increases of up to 50 % in the period between 10:00 and 20:59. This increase can probably be attributed to an increase in leisure cycling trips, which are often on weekends. On weekdays, the only positive impact on bicycle ridership is between 11:00 and 15:59, and these positive effects are not as strong as on weekends.

There are also other differences in the hour-specific changes during weekdays. Significantly fewer bicycles were counted in the morning peak during the Covid-19

pandemic. An increase in working from home and non-essential business closures are potential explanations of these results. The negative trends in bicycle traffic are further evident in the evening hours between 21:00 and 22:59. Restrictions in leisure time activities and of contacts are a potential cause of this decline.

The heterogeneity of these hourly effects is further illustrated in Figure A3 in Appendix A.A5, which plots the hour-specific effects and confidence intervals for various subsamples. In general, we can see that the effects are more positive for cities where bicycle ridership increases, and more negative for those where ridership decreases.

VI.   Estimation of Changes in the Modal Share of Cycling

While we can see that the impact of the Covid-19 pandemic on cycling varies significantly over different cities, the aforementioned results provide no information about modal shifts. As introduced in Section II.E, we can calculate the percentage point changes in modal share of cycling by combining the estimation results of cycling (Table A3), the changes in overall mobility (Table A2), which are based on a approximation of mobile phone data, and the pre-pandemic modal share in each city (Table 1).[13] The detailed mathematical calculations are available in Appendix A.A3. The results are displayed in Figure 9 for the three intervention-type variables and each city.[14]

First, the results show that the modal share of cycling increased in all cities of the sample, except for Muenster. The city of Muenster is generally considered as a classic *bicycle city* and has a very high share of students and pre-pandemic modal share of cycling. Thus, many trips were always by bike, especially to work and university. During the pandemic, bicycle ridership decreases slightly more than overall mobility, thus resulting in a negative change in the modal share of cycling for the *no_intervention_type* (−1.16 p.p) and *one_intervention_type* variable (−2.35 p.p). One reason for this could be that fewer public transport users switched to cycling than users who switched to other alternatives. To confirm this, however, further studies would be necessary.

In all other cities of the sample, the modal share of cycling increased due to the pandemic for all intervention-type variables. This change was especially pronounced in cities with an increase in cycling, with the highest modal share increases for *two_intervention_types* in Berlin (+24.99 p.p), Bonn (+15.59 p.p), and Duesseldorf (+13.51 p.p.). Based on our results, we can thus say that while contact restrictions and closures were active, the modal share of cycling in Berlin increased from about 18 % to 43 %. The resulting modal share is quite high, and roughly corresponds to the figures of Dutch bicycle cities.

In the cities of Heidelberg and Freiburg, we found a decrease in bicycle ridership, but the decrease in overall mobility was even higher. This lead to an increase of the modal share of cycling of about 8 p.p for the strictest government intervention in both cities.

In Augsburg, Hanover, Essen, and Munich, we mostly found no statistically significant change in bicycle ridership. Thus, we cannot reject the hypothesis

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[13] By assuming that bycicle ridership can be approximated by bicycle count data and that overall mobility changes can be approximated by mobile phone data, we can draw conclusions on changes in the modal share of cycling. Due to lack of data, we cannot estimate modal share changes for other modes of transport.

[14] Detailed results for percentage and percentage point changes are available in Table A1 in Appendix A.A4.
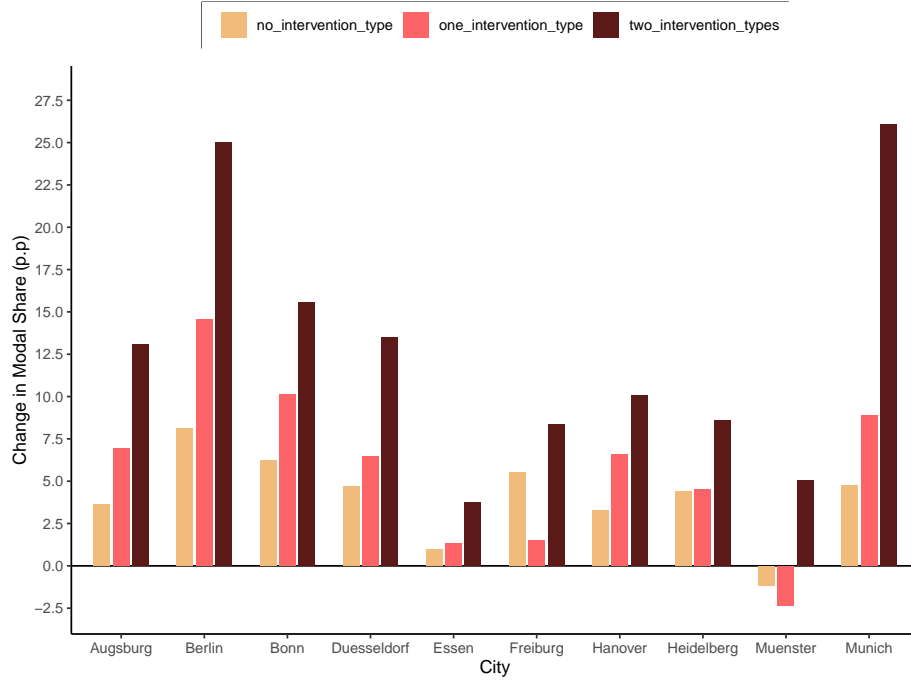
Figure 9. : Percentage Point Changes in Modal Share of Cycling

that changes in cycling during the pandemic are statistically different from zero. We therefore assume that bicycle ridership did not change in these cities when calculating modal share changes. In combination with decreases in overall mobility in all cities, we then have to infer that the modal share of cycling rises due to insignificant changes in cycling in these four cities. This procedure also drives the high increase in the modal share of cycling in Munich for *two_intervention_types* of about 26 percentage points.

Except for Hanover and Muenster, the results show that the increases in the modal share of cycling were greater under stricter government interventions. This implies a more negative impact on overall mobility than on cycling, thereby increasing the importance of the bicycle as a means of transport during the pandemic.

VII. Conclusion and Discussion

In this paper, we use data from automated pedestrian and bicycle-counting stations, as well as information on weather conditions and calendar events. This data enables us to estimate the isolated impact of the Covid-19 pandemic and subsequent government intervention on active mobility in 10 German cities during the first wave of the pandemic. Additionally, we combine overall mobility changes, and changes in bicycle ridership, in order to estimate changes in the modal share of cycling.

We find that pedestrian levels in pedestrian zones decrease with higher local incidence values, and more severe government intervention leads to stronger reductions in pedestrian levels. During all hours of the day, the pandemic impacts negatively on pedestrian flows, with the smallest decreases between 7:00 and

8:59. In general, the impact is strongest on Saturdays, and least pronounced on Sundays. It is important to note, however, that due to the locations of pedestrian counters, our results refer strictly to pedestrian traffic within city pedestrian zones, and thus cannot be extrapolated to all types of walking (e.g. not to walking in nature).

For cycling, we find that the impact of the pandemic varies substantially between cities. Bicycle ridership decreases in cities with a relatively high modal share of cycling, a high share of university students, and fewer public transport options. It increases in cities with a relatively low modal share of cycling, a lower share of students, and a well-developed public transport system. One reason could be a modal shift from public transport to cycling, which is more pronounced in cities with a higher modal share of public transport and a lower share of cycling. We also find that the pandemic impacts more positively on cycling during the midday and afternoon hours, whereas the impact is more negative in morning peak hours. On weekends, the impact is also more positive than during weekdays.

In all cities of the sample, the overall mobility of the population, which is derived from mobile phone data, consistently decreases more under more severe government interventions. When it comes to cycling, the severity of government interventions has a more ambiguous impact. For cities that observe reductions in bicycle traffic, we find that this reduction increases if government interventions are in effect. In cities where bicycle traffic increases, however, government interventions can enhance the positive impact of the pandemic on cycling.

Using data on changes in overall mobility, changes in bicycle ridership and the pre-pandemic modal shares of cycling, we estimate changes in the modal share of cycling. Except for Muenster, the city with the highest pre-pandemic modal share of cycling in our sample, the modal share of cycling increases in all cities during the pandemic. In general, these increases are greater in cities with lower modal shares of cycling, and when government interventions are in effect.

Our research has various implications for policymakers. First, government intervention such as closures of public spaces and contact restrictions are effective in restricting individual mobility, and the more severe the intervention, the higher the decline in overall mobility. Second, we see that strong growth in bicycle ridership is possible, with modal share increases of up to 25 percentage points. Policymakers should try to intensify this trend by providing an adequate and safe bicycle infrastructure, for example by converting pop-up bike lanes to permanent bike lanes that are physically separated from motorized traffic. This might be especially relevant for "new" cyclists who switched from less sustainable modes of transport.

An interesting avenue for future research would be to analyze whether the safety of pedestrians and cyclists might have been affected by the different traffic levels during the pandemic. Moreover, additional research is needed to better understand mobility changes in subsequent waves of the pandemic. Differences in the risk of infection, pandemic fatigue, and generally less severe government interventions could lead to different impacts on active mobility.
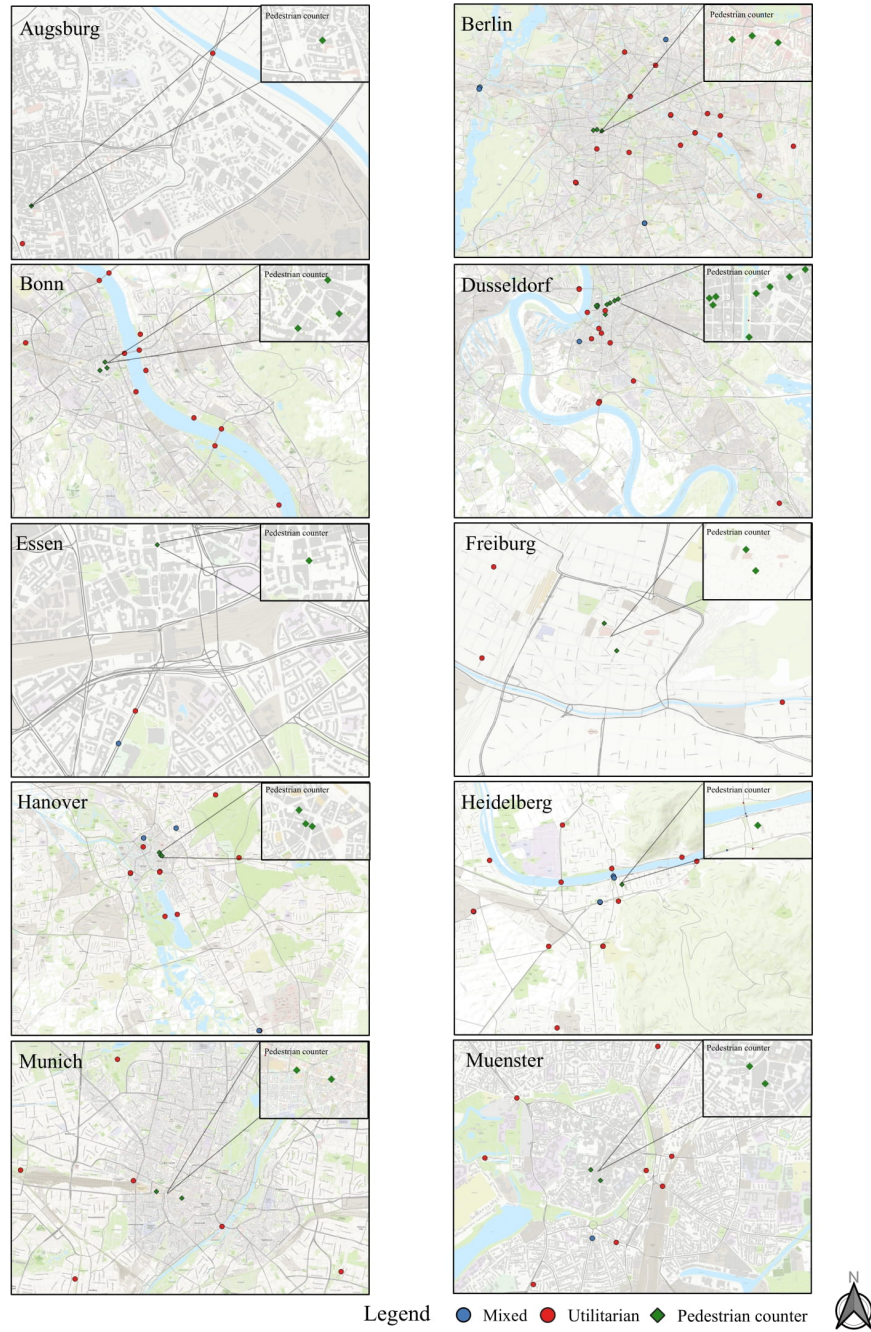
APPENDIX

A1.   Location of the Counting Stations

Figure A1. : Location of the Pedestrian and Bicycle Counting Stations

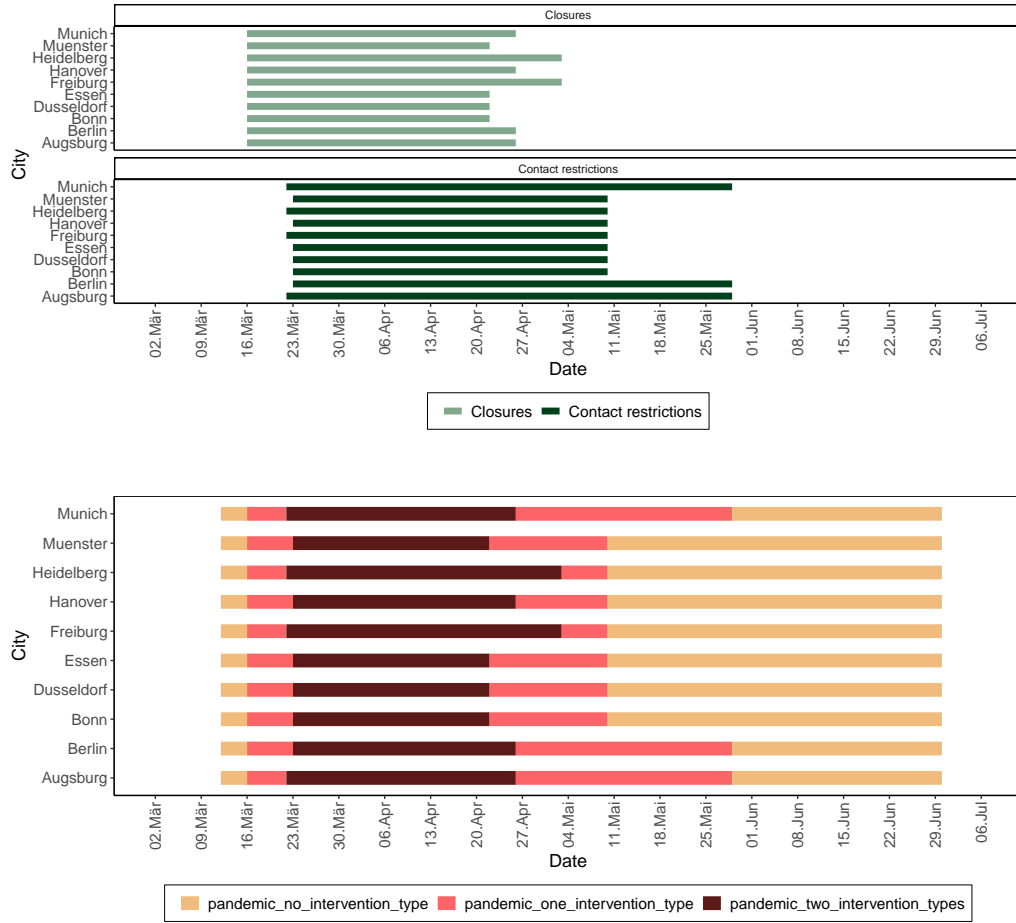*A2.   Government Interventions in Cities of the Sample*

Figure A2. : Government Interventions and Created Variables

A3.   *Mathematical Backround of Calculating Modal Share Changes*

For deriving information on city-specific modal share changes of cycling, we use the following calculations for combining estimated changes in bicycle ridership (Section V), overall mobility (Section III) and the pre-pandemic modal share.[15]

The modal share of a given transport mode i can be calculated as

$$(A1) \qquad \text{modal\_share}_i = \frac{mobility_i}{\sum_{j=1}^{n} mobility_j},$$

where $mobility_i$ is the number of trips of transport mode i, with n available transport modes and $i \in [1, \ldots, n]$. The percentage change in the modal share of transport mode i from period 0 to period 1 can then be calculated as follows:

$$(A2) \qquad \frac{\text{modal\_share}_{i1} - \text{modal\_share}_{i0}}{\text{modal\_share}_{i0}} = \frac{\frac{mobility_{i1}}{\sum_{j=1}^{n} mobility_{j1}} - \frac{mobility_{i0}}{\sum_{j=1}^{n} mobility_{j0}}}{\frac{mobility_{i0}}{\sum_{j=1}^{n} mobility_{j0}}}$$

$$(A3) \qquad = \frac{mobility_{i1}}{mobility_{i0}} * \frac{\sum_{j=1}^{n} mobility_{j0}}{\sum_{j=1}^{n} mobility_{j1}} - 1$$

$$(A4) \qquad = \frac{\frac{mobility_{i1} - mobility_{i0}}{mobility_{i0}} + 1}{\frac{\sum_{j=1}^{n} mobility_{j1} - \sum_{j=1}^{n} mobility_{j0}}{\sum_{j=1}^{n} mobility_{j0}} + 1} - 1$$

$$(A5) \qquad = \frac{\hat{\beta}_{mobility_i} + 1}{\hat{\beta}_{overall\_mobility} + 1} - 1.$$

For the change in the modal share of transport mode i in percentage points, we use the pre-pandemic modal share of transport mode i to calculate the percentage point change in modal share of transport mode i as

$$(A6) \quad \text{modal\_share}_{i1} - \text{modal\_share}_{i0} = (\frac{\hat{\beta}_{mobility_i} + 1}{\hat{\beta}_{overall\_mobility} + 1} - 1) * \text{modal\_share}_{i0}.$$

Inserting the three components then leads to the percentage point changes in cycling presented in Section VI. Detailed results for percentage and percentage point changes are available in Table A1 in Appendix A.A4.

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[15] The original modal shares are provided in the special report Mobilität in Deutschland by the Ministry of Transport (Nobis and Kuhnimhof, 2018) and is diplayed in Table 1.

A4. Modal Share Changes: Detailed Results

Table A1—: Modal Share Changes of Cycling During the Pandemic

| City	in Percent			in Percentage Points		
	No intervention	One intervention	Two interventions	No intervention	One intervention	Two interventions
Augsburg	19.05%	36.61%	68.92%	3.62	6.96	13.10
Berlin	44.98%	80.79%	138.84%	8.10	14.54	24.99
Bonn	41.57%	67.61%	103.90%	6.24	10.14	15.59
Duesseldorf	39.20%	54.08%	112.57%	4.70	6.49	13.51
Essen	13.64%	19.02%	53.37%	0.96	1.33	3.74
Freiburg	23.92%	6.65%	36.36%	5.50	1.53	8.36
Hanover	17.37%	34.62%	53.14%	3.30	6.58	10.10
Heidelberg	16.97%	17.33%	33.10%	4.41	4.51	8.61
Munich	26.26%	49.25%	144.85%	4.73	8.87	26.07
Muenster	-2.96%	-6.02%	12.89%	-1.16	-2.35	5.03

Modal share changes are calculated according to Equations A5 and A6, using estimated bicycle ridership changes from Table A3, mobility changes from Table A2, and original modal share values from Table 1.

A5. Hourly Impacts for Various Subsamples
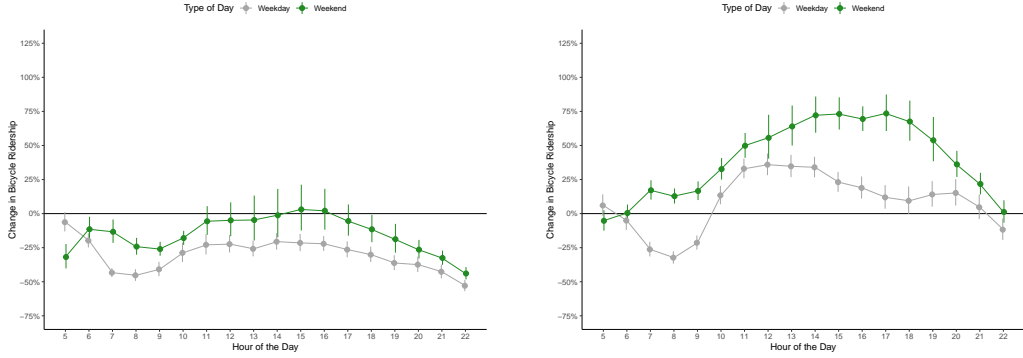
(a) Point Estimates of Hourly Covid-19 Pandemic Impact (Freiburg, Heidelberg, Muenster)

(b) Point Estimates of Hourly Covid-19 Pandemic Impact (Berlin, Bonn, Duesseldorf)
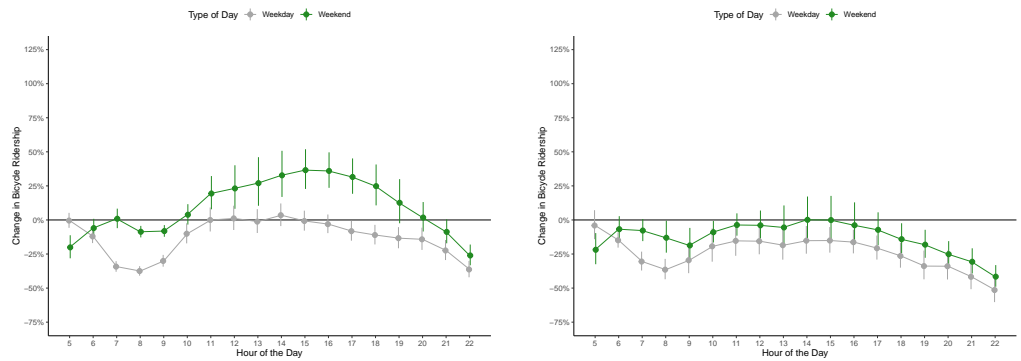
(c) Point Estimates of Hourly Covid-19 Pandemic Impact (Utilitarian Counters)

(d) Point Estimates of Hourly Covid-19 Pandemic Impact (Mixed Counters)

Figure A3. : Heterogeneity of Point Estimates of Hourly Covid-19 Pandemic Impact on Cycling

A6. Detailled Regression Results for Changes in Overall Mobility

Table A2—: City-specific Impacts of the Pandemic and Government Interventions on Overall Mobility

Dependent Variable:					mobility_change					
City:	Augsburg	Berlin	Bonn	Duesseldorf	Essen	Freiburg	Hanover	Heidelberg	Munich	Muenster
Model:	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
pandemic_no_intervention_type	-0.160***	-0.146***	-0.144***	-0.176***	-0.120***	-0.189***	-0.148***	-0.254***	-0.208***	-0.190***
	(0.026)	(0.021)	(0.019)	(0.020)	(0.019)	(0.021)	(0.017)	(0.019)	(0.024)	(0.019)
pandemic_one_intervention_type	-0.268***	-0.293***	-0.318***	-0.351***	-0.264***	-0.410***	-0.324***	-0.451***	-0.330***	-0.352***
	(0.026)	(0.019)	(0.024)	(0.024)	(0.024)	(0.033)	(0.023)	(0.029)	(0.024)	(0.024)
pandemic_two_intervention_types	-0.408***	-0.385***	-0.395***	-0.443***	-0.348***	-0.402***	-0.347***	-0.435***	-0.447***	-0.457***
	(0.026)	(0.022)	(0.028)	(0.029)	(0.026)	(0.025)	(0.022)	(0.022)	(0.024)	(0.030)
temperature_change	0.002	0.002	0.00003	0.0003	0.0003	0.001	-0.001	0.0005	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
precipitation_change	-0.037	0.035	0.001	-0.008	-0.002	0.048	-0.035	0.005	-0.033	0.034
	(0.037)	(0.042)	(0.033)	(0.041)	(0.034)	(0.040)	(0.041)	(0.028)	(0.035)	(0.041)
windspeed_change	0.003	0.006	-0.005	-0.002	-0.006	-0.007	0.0001	-0.006	0.004	-0.001
	(0.004)	(0.005)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
public_holiday_change	-0.061	-0.055*	-0.063*	-0.071*	-0.060*	-0.019	-0.117***	-0.023	-0.056	-0.078**
	(0.044)	(0.032)	(0.036)	(0.037)	(0.035)	(0.040)	(0.036)	(0.038)	(0.041)	(0.037)
school_holiday_change	-0.065***	-0.026	-0.057*	-0.044	-0.052	-0.098***	-0.066***	-0.071***	-0.061***	-0.064**
	(0.025)	(0.021)	(0.031)	(0.032)	(0.032)	(0.025)	(0.023)	(0.025)	(0.023)	(0.032)
semester_change	-0.008	-0.032	-0.066**	-0.065**	-0.067**	0.050**	-0.032	0.047*	-0.009	-0.081**
	(0.031)	(0.023)	(0.032)	(0.033)	(0.039)	(0.023)	(0.029)	(0.026)	(0.029)	(0.033)
Constant	1.020***	1.001***	0.969***	0.951***	0.997***	1.077***	0.975***	1.017***	1.007***	1.004***
	(0.019)	(0.014)	(0.015)	(0.015)	(0.015)	(0.017)	(0.013)	(0.016)	(0.017)	(0.015)
Counter-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour×Weekday-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	151	151	151	151	151	151	151	151	151	151
R²	0.706	0.775	0.745	0.775	0.700	0.779	0.764	0.808	0.780	0.789
Adjusted R²	0.687	0.761	0.728	0.761	0.681	0.765	0.749	0.796	0.766	0.775

Two-way (Counter & Hour×Weekday) standard-errors in parentheses.
Significance Levels: ***: 0.01, **: 0.05, *: 0.1.

A7. *Detailled Regression Results for Changes in Bicycle Ridership*

Table A3—: City-specific Impacts of the Pandemic and Government Interventions on Cycling

Dependent Variable:	ln(bicycle.counts)									
City:	Augsburg	Berlin	Bonn	Duesseldorf	Essen	Freiburg	Hanover	Heidelberg	Munich	Muenster
Model:	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
pandemic_no_intervention_type	-0.0005	0.1897***	0.2159***	0.1372***	0.0055	-0.2671	0.0237	-0.1181**	0.1877	-0.2412***
	(0.0756)	(0.0250)	(0.0486)	(0.0377)	(0.0318)	(0.2379)	(0.0331)	(0.0476)	(0.1440)	(0.0477)
pandemic_one_intervention_type	-0.0944	0.1695***	0.2095***	0.0758	-0.1329**	-0.4180***	-0.0942*	-0.3409***	0.1605	-0.4963***
	(0.1129)	(0.0352)	(0.0775)	(0.0622)	(0.0521)	(0.1594)	(0.0503)	(0.0609)	(0.1487)	(0.0566)
pandemic_two_intervention_types	-0.0982	0.2264***	0.3679***	0.1690**	-0.0130	-0.2481***	-0.0428	-0.2900***	0.3034*	-0.4886***
	(0.1299)	(0.0556)	(0.0859)	(0.0841)	(0.0623)	(0.0802)	(0.0789)	(0.0752)	(0.1507)	(0.0505)
public_holidays	-0.6735***	-0.4255***	-0.1773	-0.5299***	-0.7223***	-0.6497***	-0.5836***	-0.6401***	-0.3724***	-0.7950***
	(0.1981)	(0.0634)	(0.1129)	(0.1158)	(0.1210)	(0.0621)	(0.0901)	(0.0743)	(0.0979)	(0.0595)
school_holidays	-0.1835***	-0.1895***	-0.1581***	-0.1686***	-0.1940***	-0.2372***	-0.1695***	-0.1994***	-0.2071***	-0.2019***
	(0.0347)	(0.0170)	(0.0169)	(0.0344)	(0.0162)	(0.0226)	(0.0282)	(0.0182)	(0.0213)	(0.0143)
semester	0.0188	0.0441***	0.0821***	0.0798***	0.0713***	0.0114	0.0482***	0.1383***	0.0388	0.1115***
	(0.0201)	(0.0090)	(0.0106)	(0.0193)	(0.0073)	(0.0611)	(0.0183)	(0.0137)	(0.0298)	(0.0267)
temperature	51.41***	149.1***	127.3***	113.0***	38.25***	43.67***	95.01***	82.91***	110.5***	40.73***
	(3.300)	(7.239)	(12.75)	(9.229)	(1.711)	(4.369)	(6.145)	(6.238)	(4.637)	(2.156)
temperature^2	-6.525***	-29.61***	-10.17***	-14.74***	-6.835***	-2.832**	-12.62***	-7.664***	-11.67***	-6.933***
	(0.7581)	(2.548)	(3.246)	(3.042)	(0.6108)	(1.188)	(2.473)	(2.157)	(3.040)	(1.323)
light_rain	-0.3578***	-0.3511***	-0.4100***	-0.3671***	-0.3656***	-0.2016***	-0.2877***	-0.2444***	-0.4316***	-0.1898***
	(0.0143)	(0.0200)	(0.0394)	(0.0375)	(0.0174)	(0.0211)	(0.0219)	(0.0191)	(0.0241)	(0.0124)
strong_rain	-0.4207***	-0.3368***	-0.4506***	-0.3636***	-0.4867***	-0.2507***	-0.4246***	-0.3493***	-0.6005***	-0.3285***
	(0.0700)	(0.0631)	(0.0904)	(0.0596)	(0.0611)	(0.0638)	(0.0837)	(0.0444)	(0.0895)	(0.0418)
wind_speed	-0.0444***	-0.0236***	-0.0624***	-0.0464***	-0.0561***	-0.0346***	-0.0304***	-0.0421***	-0.0560***	-0.0336***
	(0.0021)	(0.0018)	(0.0054)	(0.0045)	(0.0044)	(0.0037)	(0.0029)	(0.0025)	(0.0044)	(0.0022)
Counter_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hour×Weekday-FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,692	213,264	86,058	126,882	19,438	39,240	127,882	139,355	57,870	82,044
Pseudo R^2	0.15190	0.15285	0.14918	0.15184	0.15689	0.13485	0.14742	0.17157	0.16875	0.16667
Overdispersion	9.4866	5.1337	3.7390	3.5418	5.7116	6.0997	7.0997	6.0815	4.5293	11.436

Two-way (Counter & Hour×Weekday) standard-errors in parentheses.
Significance Levels: ***: 0.01, **: 0.05, *: 0.1.

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