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The impact of the Covid-19 pandemic and government intervention on active mobility

By Alessa Möllers*, Sebastian Specht* and Jan Wessel*†

With data from automated counting stations and controlling for weather and calendar effects, we estimate the isolated impacts of the Covid-19 pandemic and subsequent government intervention (contact restrictions and business closures) 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.

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 of leisure activities, or the growth in short-term work and unemployment, overall mobility decreases. If one still has to travel, the transport mode decision is now influenced by the new challenges posed by the pandemic. The risk of getting infected impacts on personal security when traveling, with varying risk levels for different travel alternatives. While contact to 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 when riding a bicycle.

In this paper we focus on active mobility, that is, walking and cycling, and how these two transport modes are affected by the Covid-19 pandemic. 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. In order

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to calculate the actual impact of the Covid-19 pandemic on mobility behavior, it is necessary to control for external factors that simultaneously impact on mobility, such as weather or calendar events. There are various papers which analyze the impact of weather on walking and cycling (e.g. Aultman-Hall et al., 2009; Miranda-Moreno and Nosal, 2011; Liu et al., 2015; Böcker et al., 2016; Ermagun et al., 2018). 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 of the impact of the Covid-19 pandemic on active mobility. In fact, actual weather data show that there were systematic differences in precipitation volumes between the first six months of 2019 and 2020 for Germany. Especially in March, April, and May of 2020, the months for which the overall impact of the Covid-19 pandemic on everyday life was arguably the most dramatic, there was 43.4 % less precipitation than in the same months of 2019 (see Figure 7 in Appendix A.A). Not correcting for this difference could bias estimated Covid-19 impacts, because less rain would c.p. lead to increased active travel.

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), academic research on the impact of Covid-19 on active mobility is still in its infancy. 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) analyze changes in various transport modes for Budapest and roughly approximate modal share changes. Moreover, a series of papers analyses the impact of Covid-19 in Australia during different phases of the pandemic (Beck and Hensher, 2020b,a). They show that in the early days of the Australian restrictions, the use of active modes decreased, and that respondents of their survey planned to further decrease their usage in the future. When asked again in the early days of the easing of restrictions, more respondents stated that they increased their usage of active transport modes.

The aforementioned studies compare active mobility before the pandemic to active mobility during the pandemic, without controlling for weather or calendar effects. Zhang and Fricker (2021) control for weather effects and use a Bayesian structural time series model to estimate the impact of Covid-19 on non-motorized transportation. They find heterogenous effects among US cities by applying a DID-estimation for daily counting data in 2020. We extend their findings by using hourly count data from automated pedestrian and bicycle counters in 10 German cities. In combination with control variables for weather and calendar events, we can provide accurate estimates of the isolated impact of the Covid-19 pandemic on walking and cycling in Germany. In contrast to Zhang and Fricker (2021), we also study the impact of government interventions and various types of impact heterogeneity, for example over different times of day. Our specific contributions to the literature are as follows.

With respect to walking in pedestrian zones, we find that pedestrian traffic decreases with increasing local incidence values. The more government interventions like business closures or contact restrictions are in effect, the less people walk in all cities within the sample. During all hours of the day, the pandemic impacts negatively on pedestrian flows. Especially the very early morning hours and the evening hours are affected. The smallest decrease is in the morning hours between 7:00 and 8:59. In general, the impact is strongest on Saturdays, and least pronounced on Sundays. It should be noted that the pedestrian counters are located in more heavily frequented pedestrian zones, thus not allowing inferences for general walking levels, including walking in nature.

With respect to bicycle traffic, the literature has shown that there are significant regional differences in attitudes towards cycling (e.g. Santos et al., 2013; Liu et al., 2014, 2015; Goldmann and Wessel, 2020). Hence, it appears reasonable to assume that cyclists in different regions would display heterogenous reactions to the Covid-19 pandemic. As noted by Shakibaei et al. (2020), bicycle usage has increased in regions with a lower modal share of cycling (Teixeira and Lopes (2020) for New York, Beck and Hensher (2020b,a) for Australia, or Nurse and Dunning (2020) for Bogota in Colombia). In the Netherlands, however, cycling has a higher modal share and bicycle usage decreased only slightly during the pandemic (de Haas et al., 2020). We thus add to the literature on regional heterogeneity by comparing the impacts of the Covid-19 pandemic on cycling for 10 German cities, using the same regression design throughout. We find that cycling increases in cities with a relatively low modal share of cycling, and that it decreases in cities with a higher share. We attribute these difference to the interplay of two opposing effects: (i) a general decrease in mobility which leads to a decrease in bicycle ridership, and (ii) potential shifts from public transport to cycling and/or increases in leisure cycling. In *bicycle cities*, the former effect appears to be stronger than the latter, while the reverse holds for non-bicycle cities.

Moreover, we study the impact of government intervention on cycling. Therefore, we differentiate between the effects during the pandemic when no government interventions were in effect, when either business closures or contact restrictions were in effect, or when both business closures and contact restrictions were in effect. For cities that observe reductions in bicycle traffic, we find that the reduction in cycling is stronger if government interventions are in effect. In cities where bicycle traffic increases, however, government intervention can enhance the positive impact of the pandemic on cycling.

We also consider how the impact of the pandemic varies over different daytimes and weekdays. In general, we find that the pandemic impacts more positively on cycling during the midday and afternoon hours, whereas the impact is more negative in the morning. On weekends, the impact is also more positive than during weekdays.

Last but not least, we contribute to the literature by calculating changes in the modal share of cycling that are caused by the Covid-19 pandemic. Accordingly, we combine changes in overall mobility that are derived from mobile phone data (Schlosser et al., 2020) with the estimated changes in bicycle ridership. We find that only in Münster, the city with the highest modal share of cycling, could a reduction in the modal share of cycling be observed, whereas it increased for the other nine cities. In general, the increase was stronger in cities with a lower modal share of cycling, as well as during stricter government interventions. This implies that stricter government interventions had 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.

The remainder of this paper is structured as follows. The data and descriptive statistics are outlined in Section II. The impact of the Covid-19 pandemic and subsequent government interventions on pedestrian counts are analyzed in Section III. The impact on bicycle ridership, as well as modal share changes in cycling are analyzed in Section IV. Section V concludes.

II. Data and Descriptive Analysis

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. Our sample comprises larger and medium sized German cities, with populations between roughly 3.7 million (Berlin) and 160,000 (Heidelberg). For all of these cities, both pedestrian and bicycle-counting data are available. The cities are chosen in such a way that they cover cities with a high modal share of cycling, as well as cities with a low modal share. Moreover, these cities lie 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		Modal Share			Bicycle City Rankings		Public Transport			Pop. Dens.[1]	Young People Share	
	Pedestrian	Bicycle	Walking	Bicycle	Public Transport	ADFC (2019)[2]	Weather (2020)[3]	Subway	S-Train	Tram		age < 18	age < 25
Augsburg	1	2	31%	19%	16%	5	8	No	No	Yes	2020	15,4 %	24,5 %
Berlin	3	23	30%	18%	27%	10	5	Yes	Yes	Yes	4115	16,5 %	23,7 %
Bonn	3	11	28%	15%	17%	7	7	Yes	Yes	Yes	2337	17,3 %	27,4 %
Düsseldorf	8	14	29%	12%	19%	8	9	Yes	Yes	Yes	2860	16,1 %	23,2 %
Essen	1	4	19%	7%	19%	9	4	Yes	No	Yes	2771	13,3 %	21,0 %
Freiburg	2	4	27%	23%	17%	2	3	No	No	Yes	1511	15,9 %	20,7 %
Hanover	3	13	27%	19%	20%	4	6	Yes	Yes	Yes	2630	15,7 %	25,0 %
Heidelberg	1	18	26%	26%	13%	3	2	No	Yes	Yes	1484	14,4 %	27,7 %
Munich	2	6	24%	18%	24%	6	10	Yes	Yes	Yes	4777	15,9 %	24,0 %
Münster	2	9	22%	39%	10%	1	1	No	No	No	1040	15,0 %	27,3 %

[1] In population per square kilometer.
[2] Based on the overall grades of the ADFC Bicycle Climate Index. Only the cities of our sample are considered for this ranking.
[3] Based on the weather elasticities from Goldmann and Wessel (2020). Only the cities of our sample are considered for this ranking.

B. *Covid-19 data, Weather Data and Calendar Events*

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). Consequently, the presented results hereinafter are valid for the first wave of the Covid-19 pandemic in Germany. 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 wave.

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 taken 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. These interventions include contact restrictions and business closures. We define contact restrictions to be in effect if there are either curfew restrictions, or if meetings with more than one person from another household are not allowed. Business closures are in effect if the government prohibited businesses from opening. An overview of the periods during which such interventions were in effect can be found in Figure 8 in Appendix A.B.

In order to accurately capture the impact of the pandemic and government interventions, we create three separate dummy variables. The variable *pandemic_no_intervention* refers to days during the Covid-19 pandemic for which no government interventions were in effect. The variable *pandemic_one_intervention* refers to days during the Covid-19 pandemic for which either business closures or contact restrictions were in effect. Finally, the variable *pandemic_two_interventions* refers to days during the pandemic for which businesses were closed and contacts restricted.[1] The reference category is then the time outside the pandemic. We exploit the regional variation in timing of government intervention, which were often implemented at the state-level, in order to identify the impacts of different lockdown situations. During the pandemic, about half of the observations are without active government interventions, one quarter are with one intervention, and one quarter with two.

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 ($0\,\text{mm} < \text{precipitation} < 2.5\,\text{mm}$), and one for stronger rain ($\text{precipitation} \geq 2.5\,\text{mm}$). The weather data are from the nearest weather stations of the Deutscher Wetterdienst (DWD). Additional dummy variables account for school holidays, public holidays and university semesters.

C. Pedestrian Traffic

In order to analyze the effect of the Covid-19 pandemic on pedestrian traffic, we use hourly pedestrian counts from 26 automated counting stations in 10 German cities.[2] The counting stations are installed and provided by Hystreet, a mobility start-up that focuses on passenger traffic flows in pedestrian zones of medium and large 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.

Figure 1 displays the average number of counted pedestrian per hour, separated over the first 26 weeks of 2019 and 2020. We can see that 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). In general, public holidays and the accompanying business closures are often associated with lower walking levels within cities.

The dashed line between Weeks 11 and 12 represents the official beginning of the Covid-19 pandemic according to the WHO, which was followed by stricter government interventions, including store closures in Week 12. There is a visible decline in pedestrian counts during Weeks 10 and 18. Hence, pedestrian levels

[1] Although there were also other restrictions in effect to limit the spread of the Covid-19 pandemic (e.g. school closures, the closure of bars and restaurants, or the closure of museums, zoos, or libraries), we focus on two interventions that most likely affected the entire population. Thus, these two interventions arguably had the greatest impact on mobility, which is also indicated by the estimated overall mobility changes in Section IV.C.

[2] 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.

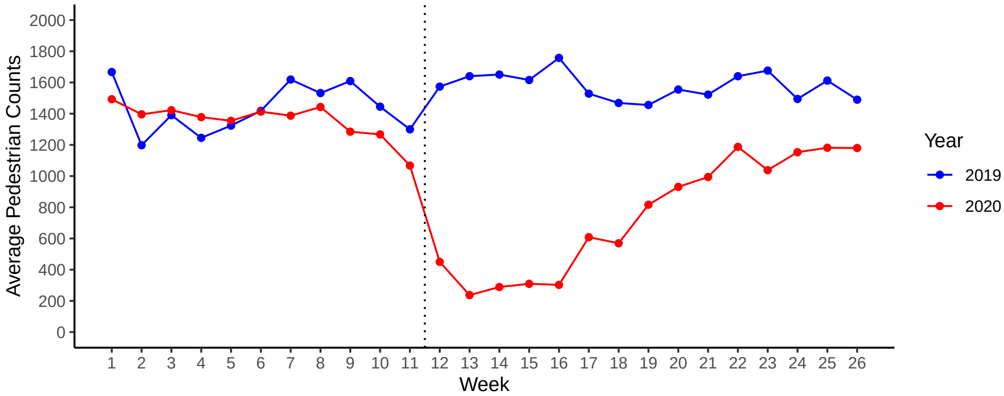

Figure 1. : Average Pedestrian Counts per Hour in 2019 and 2020

decreased even two weeks before the German government officially ordered store 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 stores 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 observation period.

As the pedestrian counting stations are installed in pedestrian zones, they are determined significantly by the weekdays and opening hours of the stores. Figure 2 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 Covid-19 pandemic from March 12, 2020, to June 30, 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, significantly 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, usually between 8:00 and 10:00, and close between 18:00 and 20:00.

There is a clearly discernable 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%.

D. Cycling

The bicycle counting stations are installed by Eco-Counter and hourly bicycle traffic is measured with the help of below-surface induction loops.[3]

In Figure 3, 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

[3] The data are propriety of the cities in the sample. We greatly appreciate the provision of the data by these cities.

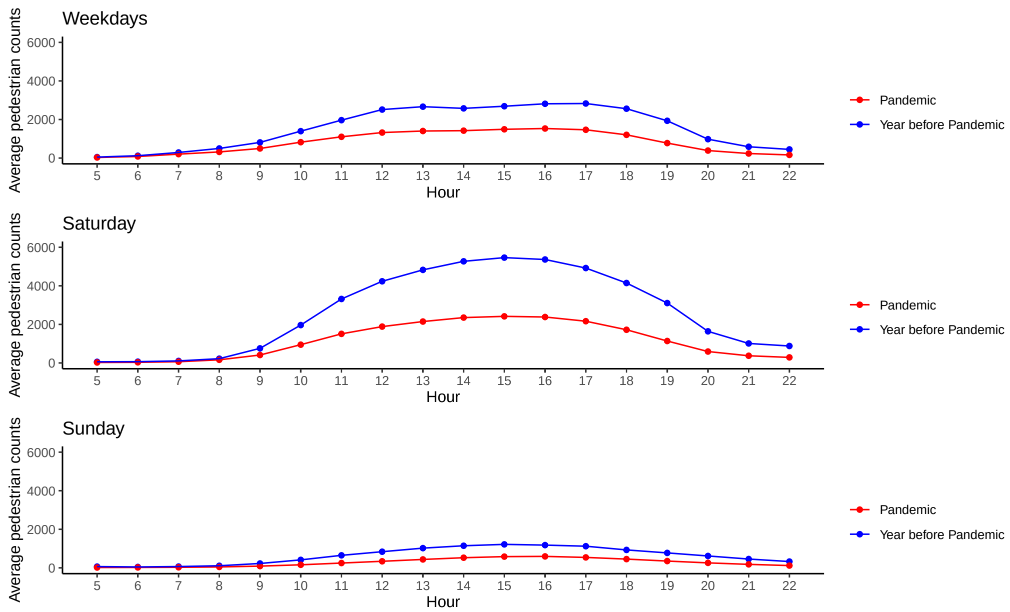

Figure 2. : Average Pedestrian Counts per Hour Before and During Pandemic

great volatility. In some weeks, the 2020 counts exceed those of the previous year, whereas they are lower in other weeks. Thus, a significant decrease in cycling is only evident for the immediate weeks after the outbreak of the pandemic. After this, there is no clear effect.

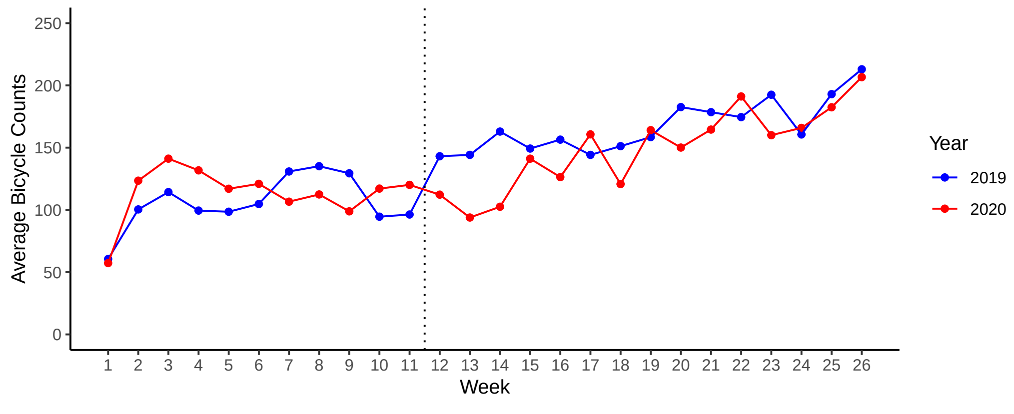

Figure 3. : Average Bicycle Counts per Hour in 2019 and 2020

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 4 presents 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.

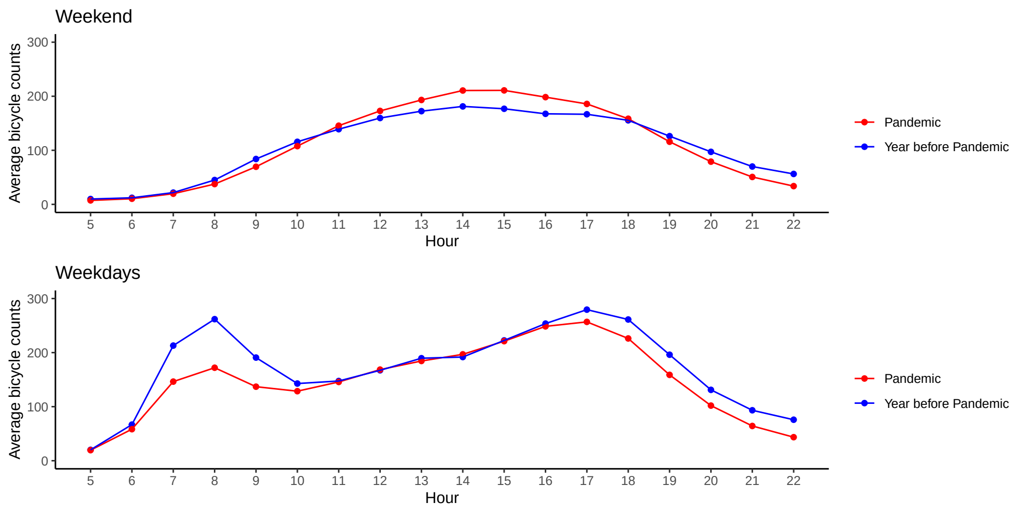

Figure 4. : Average Bicycle Counts per Hour Before and During Pandemic

While walking in pedestrian zones decreases significantly in every city, the impact of the pandemic on bicycle ridership appears to vary significantly between the cities of the sample. Table 2 outlines these changes. In bicycle-friendly cities with a higher modal share of cycling, such as Münster, 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, Düsseldorf, or Bonn. The impact heterogeneity on cycling levels across German cities will be analyzed further in Section IV.

III. Analysis of Changes in Pedestrian Traffic in Pedestrian Zones

A. *The Impact of the Pandemic and Government Intervention*

As outlined in the introduction, it is important to control for weather and calendar effects in order to estimate the isolated effect of the pandemic and subsequent governmental interventions. Therefore, we use log-linear regression models that account for weather and calendar effects at all times. Moreover, counting station fixed-effects and hour×weekday fixed-effects are included to control for idiosyncrasies of different counter locations, as well as time effects. The results for the impact of the pandemic on pedestrian traffic in pedestrian zones are then outlined in Table 3.

Model (1) uses the local *incidence_value* as regressor. 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. Our analysis in (1) shows that if one more person per 100,000 inhabitants was infected within in the last 7 days, about 3.3 % fewer pedestrians are counted. It should be noted that

Table 2—: City-Specific Changes in Pedestrian and Bicycle Traffic

City	Pedestrians (in %)	Bicycles (in %)
Augsburg	-40.6	-8.4
Berlin	-59.1	2.7
Bonn	-44.6	17.1
Düsseldorf	-49.7	26.6
Essen	-45.9	50.6
Freiburg	-47.0	-20.9
Hanover	-50.6	-3.0
Heidelberg	-51.2	-36.7
Munich	-64.2	8.2
Münster	-44.9	-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.

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.

Additionally, incidence values correlated with stricter government intervention, so that not controlling for intervention would create a potential bias in our estimate. By including the three dummy variables that control for the strength of governmental interventions in model (2), the impact of the incidence value then changes to 0.75 %. The coefficients for the dummy variables show that walking volumes decreased by 33.1 % during the first wave of the pandemic for which no governmental interventions 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.

Tougher government interventions, however, reduce the number of pedestrians even further. If either store closures or contact restrictions were in effect, pedestrian volumes decreased by roughly 60%, and if both interventions were in effect, even by 71%. This implies that government interventions were in fact effective in reducing pedestrian levels in pedestrian zones. Since just a few essential stores 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 II.C, we saw that the highest pedestrian levels can be found on Saturdays, followed by weekdays and Sundays. Therefore, we run regression model (2) again for separate subsamples of different types of days, resulting in regression models (3), (4), and (5). 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 (5). If government interventions are in effect, however, the highest decreases occur on Saturdays, with a reduction of 69.7 % in the case of one intervention, and a reduction of 78.2 % with two interventions (4). Since

Table 3—: Walking Regressions

Dependent Variable:	log(pedestrian_counts)				
Subsample:	All	All	Weekdays	Saturday	Sunday
Model:	(1)	(2)	(3)	(4)	(5)
incidence_value	-0.0337***	-0.0075***	-0.0061***	-0.0119***	-0.0077***
	(0.0035)	(0.0016)	(0.0015)	(0.0024)	(0.0020)
pandemic_no_intervention		-0.4025***	-0.3644***	-0.4301***	-0.5778***
		(0.0424)	(0.0431)	(0.0559)	(0.0546)
pandemic_one_intervention		-0.9268***	-0.8478***	-1.195***	-1.036***
		(0.0586)	(0.0596)	(0.1220)	(0.0781)
pandemic_two_interventions		-1.241***	-1.296***	-1.523***	-1.045***
		(0.0769)	(0.0816)	(0.1315)	(0.0888)
temperature	15.79***	25.69***	20.15***	7.08**	12.56***
	(4.961)	(4.068)	(3.668)	(2.462)	(3.498)
temperature^2	-10.1***	-22.52***	-15.05***	-9.375***	-18.24***
	(2.915)	(2.805)	(2.67)	(2.101)	(2.304)
light_rain	-0.2697***	-0.2953***	-0.2671***	-0.2528***	-0.4363***
	(0.0273)	(0.0253)	(0.0239)	(0.0270)	(0.0389)
stronger_rain	-0.4364***	-0.4567***	-0.3844***	-0.4672***	-0.6800***
	(0.0529)	(0.0535)	(0.0550)	(0.0985)	(0.0764)
windspeed	-0.0107***	-0.0144***	-0.0118***	-0.0166***	-0.0271***
	(0.0018)	(0.0016)	(0.0016)	(0.0036)	(0.0048)
public_holiday	-1.067***	-1.009***	-1.1***		-0.0623
	(0.0942)	(0.0948)	(0.0974)		(0.0491)
school_holiday	-0.0050	-0.0118	0.0150	-0.0961***	-0.0594*
	(0.0191)	(0.0184)	(0.0209)	(0.0163)	(0.0322)
semester	0.0766***	0.1078***	0.1071***	0.1226***	0.1076***
	(0.0229)	(0.0156)	(0.0147)	(0.0256)	(0.0297)
Counter-FE	Yes	Yes	Yes	Yes	Yes
Hour×Weekday-FE	Yes	Yes	Yes	Yes	Yes
Observations	234,472	234,472	167,664	33,420	33,388
R^2	0.889555	0.906468	0.908974	0.931109	0.882983

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

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 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.[4]

B. 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 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 5 plots the 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.[5] In Figure 5, the original point estimates and confidence intervals are already transformed by $e^{\hat{\beta}} - 1$ in order to obtain the actual percentage changes.

We find that all estimates are negative, implying that pedestrian levels in the 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. The results also show that, for all types of days, the reduction in pedestrian traffic is stronger in the evening hours than in the afternoon. 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.

IV. Analysis of Changes in Bicycle Ridership

A. Impact Heterogeneity Between Cities

As outlined in the introduction, attitudes towards cycling vary significantly across German cities, as outlined for example by the ADFC Bicycle Climate Index or by Goldmann and Wessel (2020). Due to this pre-existing heterogeneity between cities, we run regression models with the three dummy variables on the pandemic and government interventions, as well as with the usual control

[4] The results for city-specific regressions are available upon request.
[5] Detailed regression results for the hour-specific regression are available upon request.

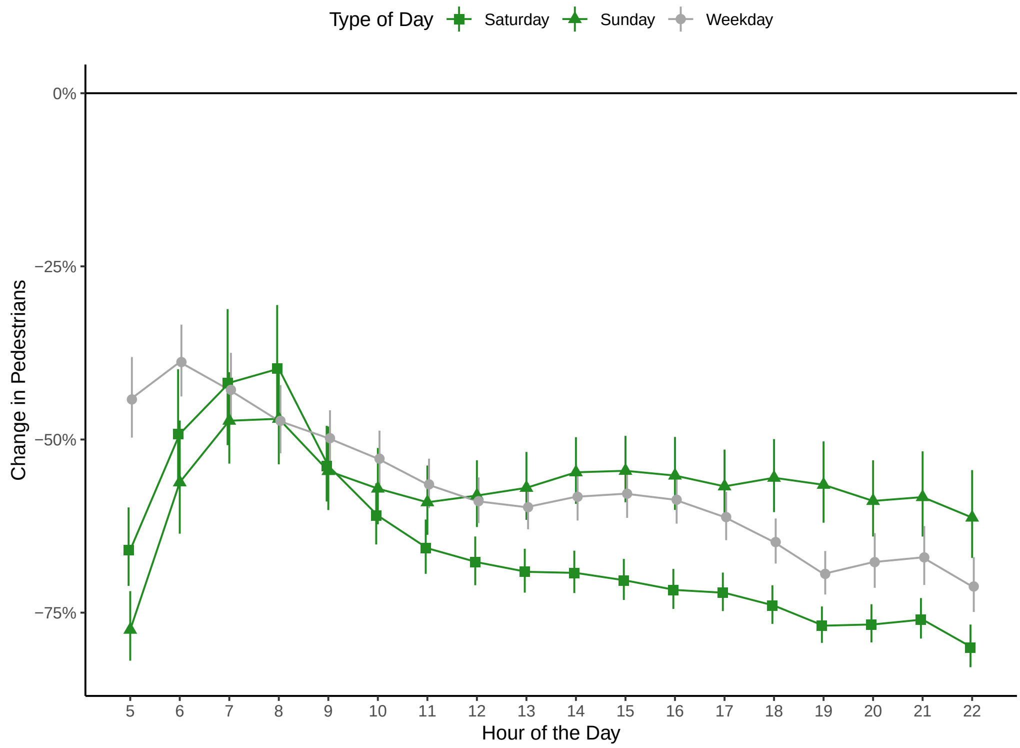

Figure 5. : Point Estimates of Hourly Covid-19 Pandemic Impact on Walking

variables and fixed effects, separately for each city in the sample. Thereby, we can analyze whether cyclists react similarly to the pandemic and government interventions, or whether there is significant heterogeneity between cities. The results are presented in Table 4.

We find evidence of the assumed heterogeneity between the ten considered cities. In general, cities with a lower modal share of cycling, such as Berlin, Bonn, and Düsseldorf, have significantly more bicycle traffic during the pandemic. While a harder lockdown did not further increase bicycle ridership in Berlin and Düsseldorf, the increase in Bonn's bicycle ridership was much greater on days when both business closures and contact restrictions were in effect.

In the cities of Münster, Heidelberg, and Freiburg, the opposite effects can be found. For Münster, bicycle ridership declined by 22.3 % on days in the pandemic when no government interventions were in effect. The introduction of a government intervention reduced bicycle ridership even further, by roughly 41 %. For Heidelberg, we can also see a reduction in bicycle ridership, with the strongest effect for days with one government intervention. In Freiburg, we only find negative effects on bicycle ridership for pandemic days with at least one government intervention in effect.

The results thus 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. The cities in which bicycle ridership decreases are also generally regarded as German *bicycle*

Table 4—: City-specific Impacts of the Pandemic and Government Interventions on Cycling

Dependent Variable:	ln(bicycle_counts)									
City:	Augsburg	Berlin	Bonn	Düsseldorf	Essen	Freiburg	Hanover	Heidelberg	Munich	Münster
Model:	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
pandemic_no_intervention	-0.0082	0.1855***	0.1896***	0.1798***	0.2257	-0.5877	0.0249	-0.1672***	0.1596	-0.2521***
	(0.0831)	(0.0296)	(0.0399)	(0.0446)	(0.1240)	(0.4883)	(0.0336)	(0.0486)	(0.1269)	(0.0485)
pandemic_one_intervention	-0.1124	0.1724***	0.2128**	0.1338*	0.2093	-0.3617**	-0.0988*	-0.4186***	0.1180	-0.5400***
	(0.1186)	(0.0370)	(0.0841)	(0.0720)	(0.1926)	(0.0856)	(0.0509)	(0.0726)	(0.1453)	(0.0602)
pandemic_two_interventions	-0.1443	0.1662***	0.4325***	0.1988**	0.4205	-0.2972*	-0.0677	-0.3203***	0.2028	-0.5236***
	(0.1383)	(0.0509)	(0.1071)	(0.0908)	(0.2383)	(0.0972)	(0.0885)	(0.0801)	(0.1525)	(0.0497)
temperature	53.27**	153.3***	169.1***	134.2***	86.12**	45.30***	95.84***	92.93***	115.4***	43.76***
	(2.914)	(11.32)	(18.04)	(13.35)	(16.29)	(4.030)	(5.988)	(6.917)	(3.386)	(2.590)
temperature^2	-6.509*	-31.05***	-16.03***	-17.87***	-12.49**	-2.603**	-13.92***	-8.713***	-13.62***	-7.169***
	(0.9317)	(3.908)	(3.378)	(3.088)	(3.534)	(0.6242)	(3.151)	(2.194)	(3.023)	(1.340)
light_rain	-0.3896**	-0.3921***	-0.4657***	-0.4289***	-0.5219***	-0.2135***	-0.3279***	-0.2636***	-0.4967***	-0.2082***
	(0.0198)	(0.0244)	(0.0398)	(0.0490)	(0.0758)	(0.0234)	(0.0244)	(0.0223)	(0.0309)	(0.0147)
stronger_rain	-0.5073*	-0.4378***	-0.5705***	-0.4769***	-0.6824***	-0.3125**	-0.5292***	-0.3818***	-0.6511***	-0.3770***
	(0.0615)	(0.0673)	(0.1028)	(0.0938)	(0.0951)	(0.0541)	(0.0824)	(0.0505)	(0.0888)	(0.0509)
windspeed	-0.0505**	-0.0248***	-0.0760***	-0.0586***	-0.0775***	-0.0347***	-0.0323***	-0.0474***	-0.0608***	-0.0365***
	(0.0025)	(0.0025)	(0.0062)	(0.0075)	(0.0101)	(0.0035)	(0.0031)	(0.0030)	(0.0052)	(0.0025)
public_holiday	-0.9358	-0.7448***	-0.5257***	-0.8033***	-0.6570**	-0.8281***	-0.8930***	-0.8694***	-0.7487***	-1.036***
	(0.1843)	(0.0868)	(0.1368)	(0.1169)	(0.1645)	(0.0919)	(0.1017)	(0.0815)	(0.1115)	(0.0818)
school_holiday	-0.2172	-0.2246***	-0.1688***	-0.1868***	-0.1940***	-0.2732***	-0.2179***	-0.2320***	-0.2423***	-0.2431***
	(0.0398)	(0.0247)	(0.0256)	(0.0365)	(0.0273)	(0.0166)	(0.0394)	(0.0205)	(0.0264)	(0.0192)
semester	0.0007	0.0384***	0.1504***	0.0792***	0.0811**	-0.0241	0.0603**	0.1289***	0.0090	0.1104***
	(0.0209)	(0.0107)	(0.0359)	(0.0186)	(0.0147)	(0.1004)	(0.0272)	(0.0146)	(0.0276)	(0.0252)
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	105,750	136,728	39,130	39,240	127,882	139,355	57,870	82,044
R^2	0.82883	0.80414	0.79332	0.73561	0.70413	0.79407	0.81906	0.86759	0.84332	0.89785

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

cities. Moreover, these cities have lower population densities and no subway system. Thus, it could be argued that there are fewer people switching from public transport to cycling in these cities.

In cities with a lower modal share of cycling, the Covid-19 pandemic has led to more people using and discovering cycling. Moreover, these cities are more densely populated and have 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 people, and hence, a heightened risk of infection with Covid-19. Furthermore, cities like Berlin and Düsseldorf have installed pop-up bike lanes during the pandemic, which may also have contributed to an increase in cycling (Kraus and Koch, 2021). Moreover, cycling could be used more and more for recreational activities, as, for example, gyms were closed and many team sports temporarily restricted.

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

In Augsburg, Essen, and Munich, no 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 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 IV.C.

B. 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 III.B, without the distinction between Saturdays and Sundays. Figure 6 plots the hourly effects and confidence intervals for such a regression model. Again, the actual point estimates and confidence intervals are already transformed by $e^{\hat{\beta}} - 1$.

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 recreational 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 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 9 in Appendix A.C, which plots the hour-specific effects and confidence intervals for

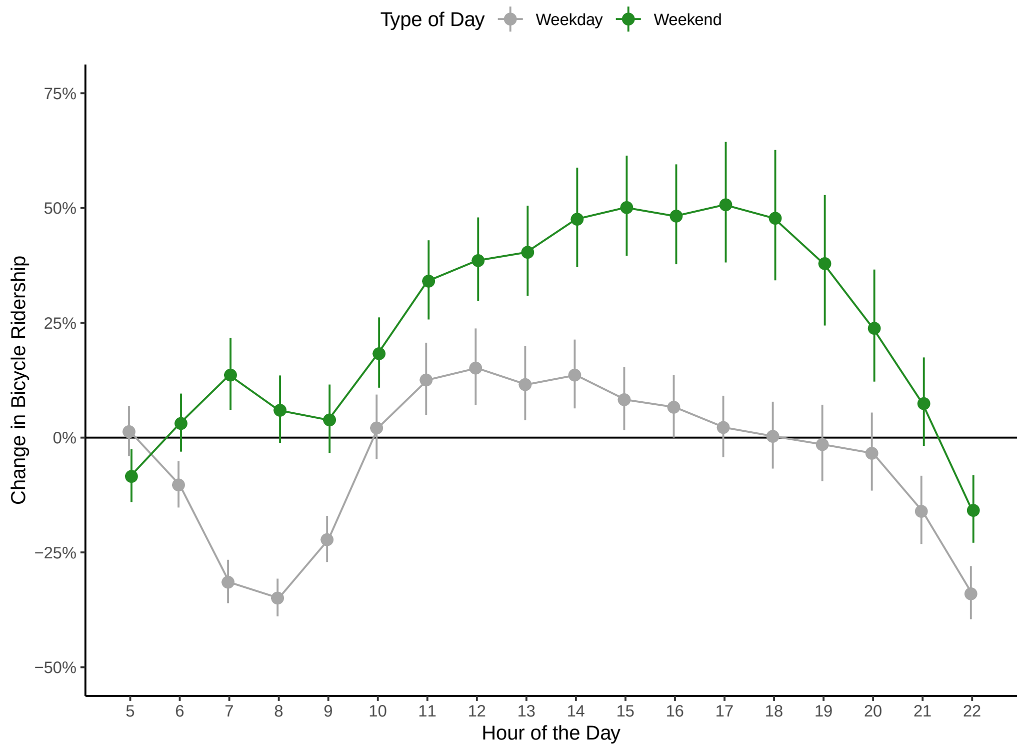

Figure 6. : Point Estimates of Hourly Covid-19 Pandemic Impact on Cycling

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. When comparing different types of bicycle-counting stations, we can see that there are very substantial increases for recreational counting stations, further underling the increased bicycle use of leisure activities.[6]

C. Estimations of Changes in the Modal Share of Cycling

Changes in Overall Mobility

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. In order to calculate city-specific modal shifts, we now use mobile phone data to approximate changes in overall mobility.

Schlosser et al. (2020) provide freely available data on overall mobility changes in German NUTS3 regions. Mobility changes are based on the changes in movements that are deduced from mobile phone data. 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

$$\frac{mobility_{i,t}}{mobility_{i,t^*}} - 1, \tag{1}$$

[6] The classification of bicycle counters is conducted according to Wessel (2020).

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.

While this already offers a good approximation of the impact of the Covid-19 pandemic on mobility, the given mobility changes might still be distorted by differences in the occurrence of calendar events or in weather conditions between the timeframe t and the comparable timeframe t^*. April 2020, for example, was uncommonly dry and hot, which could have led to an increase in active mobility. 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:

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

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

Next, we can regress the mobility change on the corresponding changes in the mobility determinants outlined above, as well as on city-specific dummy variables for the Covid-19 pandemic. Thus, the variable *Berlin_Covid* would take on the value 1 for observations from Berlin that were collected on or after March 12, 2020, and otherwise 0. The regression results with the undistorted impacts of the Covid-19 pandemic on overall mobility in the considered regions are presented in Table 5.

We can see that there is a clear pattern with respect to the impact of the pandemic and subsequent government interventions on overall mobility. For the days of the pandemic on which no government interventions were in effect, mobility decreases significantly and these decreases lie between 12.7 % in Essen and 24.4 % in Heidelberg. If either businesses are closed or contacts were restricted, mobility drops between 23,0 % in Essen and 34.4 % in Heidelberg. The reduction in mobility is most pronounced when both business closures and contact restrictions are in effect. The accompanying decline in mobility ranges between 32,0 % in Hanover and 40.1 % in Münster.

Changes in the Modal Share of Cycling

Next, we use the estimated changes in bicycle ridership and overall mobility, in order to derive information on city-specific changes in the modal share of cycling.[7] For this purpose, we use the following calculations.

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

$$\text{modal\_share}_i = \frac{mobility_i}{\sum_{j=1}^{n} mobility_j}, \tag{3}$$

[7] For two reasons, we refrain from calculating similar city-specific modal share changes of walking. First, there are only minor differences between cities, thus reducing the informational value of such an analysis. Second, and more importantly, our counter data only capture pedestrian traffic in pedestrian zones. Thus, we have no information on walking in nature or other types of walking, and subsequently cannot calculate meaningful changes in the modal share of the transport mode walking.

Table 5—: City-specific Impacts of the Pandemic and Government Interventions on Overall Mobility

Dependent Variable:	mobility_change									
City:	Augsburg	Berlin	Bonn	Düsseldorf	Essen	Freiburg	Hanover	Heidelberg	Munich	Münster
Model:	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
pandemic_no_intervention	−0.161***	−0.145***	−0.153***	−0.187***	−0.136***	−0.207***	−0.152***	−0.280***	−0.200***	−0.209***
	(0.019)	(0.017)	(0.016)	(0.016)	(0.015)	(0.018)	(0.014)	(0.017)	(0.018)	(0.016)
pandemic_one_intervention	−0.294***	−0.302***	−0.308***	−0.345***	−0.261***	−0.408***	−0.322***	−0.422***	−0.348***	−0.363***
	(0.019)	(0.016)	(0.020)	(0.020)	(0.018)	(0.031)	(0.018)	(0.030)	(0.019)	(0.020)
pandemic_two_interventions	−0.440***	−0.426***	−0.429***	−0.490***	−0.394***	−0.449***	−0.386***	−0.480***	−0.471***	−0.513***
	(0.019)	(0.021)	(0.027)	(0.027)	(0.023)	(0.023)	(0.021)	(0.024)	(0.018)	(0.027)
temperature_change	0.007***	0.007***	0.002	0.002	0.002*	0.006***	0.005***	0.003*	0.007***	0.003*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
precipitation_change	−0.106***	−0.042	0.013	−0.026	−0.026	−0.078**	−0.067**	−0.035	−0.089***	−0.066*
	(0.027)	(0.034)	(0.029)	(0.034)	(0.027)	(0.035)	(0.033)	(0.026)	(0.027)	(0.034)
windspeed_change	−0.004	0.002	−0.009**	−0.004	−0.011***	−0.010**	−0.004	−0.010**	−0.002	−0.004
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
public_holiday_change	−0.264***	−0.158***	−0.222***	−0.235***	−0.239***	−0.229***	−0.223***	−0.234***	−0.210***	−0.228***
	(0.032)	(0.027)	(0.031)	(0.030)	(0.028)	(0.034)	(0.029)	(0.034)	(0.031)	(0.030)
school_holiday_change	−0.036**	−0.026	−0.006	0.012	−0.004	−0.023	−0.071***	−0.004	−0.035**	−0.022
	(0.018)	(0.017)	(0.026)	(0.026)	(0.024)	(0.022)	(0.019)	(0.023)	(0.017)	(0.026)
semester_change	0.040*	−0.062***	−0.077***	−0.087***	−0.084**	0.117***	−0.066**	0.027	0.027	−0.102***
	(0.022)	(0.020)	(0.029)	(0.029)	(0.033)	(0.020)	(0.027)	(0.027)	(0.022)	(0.029)
Constant	0.036***	0.011	−0.026**	−0.042***	0.008	0.082***	−0.018	0.027*	0.017	0.018
	(0.013)	(0.011)	(0.013)	(0.013)	(0.012)	(0.015)	(0.011)	(0.015)	(0.013)	(0.013)
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
Adjusted R^2	0.839	0.840	0.801	0.837	0.806	0.824	0.839	0.824	0.859	0.845

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

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:

$$\frac{\text{modal\_share}_{i1} - \text{modal\_share}_{i0}}{\text{modal\_share}_{i0}} = \frac{\frac{mobility_{i1}}{\sum_{j=1}^{n} mobility_{j1}} - \frac{mobility_{i0}}{\sum_{j=1}^{n} mobility_{j0}}}{\frac{mobility_{i0}}{\sum_{j=1}^{n} mobility_{j0}}} \tag{4}$$

$$= \frac{mobility_{i1}}{mobility_{i0}} * \frac{\sum_{j=1}^{n} mobility_{j0}}{\sum_{j=1}^{n} mobility_{j1}} - 1 \tag{5}$$

$$= \frac{\frac{mobility_{i1} - mobility_{i0}}{mobility_{i0}} + 1}{\frac{\sum_{j=1}^{n} mobility_{j1} - \sum_{j=1}^{n} mobility_{j0}}{\sum_{j=1}^{n} mobility_{j0}} + 1} - 1 \tag{6}$$

$$= \frac{\hat{\beta}_{mobility_i} + 1}{\hat{\beta}_{overall\_mobility} + 1} - 1. \tag{7}$$

For the change in the modal share of transport mode i in percentage points, we need additional information on the original modal share of transport mode i. If this information is available, we can calculate the percentage point change in modal share of transport mode i as

$$\text{modal\_share}_{i1} - \text{modal\_share}_{i0} = \left(\frac{\hat{\beta}_{mobility_i} + 1}{\hat{\beta}_{overall\_mobility} + 1} - 1\right) * \text{modal\_share}_{i0}. \tag{8}$$

Now, we can use the estimated city-specific changes in bicycle ridership (Table 4) and overall mobility (Table 5), in order to calculate changes in the modal shares of cycling. The results are displayed in Table 6.

Table 6—: 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	17,51%	34,23%	55,28%	3,33	6,50	10,50
Berlin	39,19%	60,76%	80,86%	7,05	10,94	14,55
Bonn	40,91%	68,30%	136,71%	6,14	10,25	20,51
Düsseldorf	44,39%	61,44%	99,02%	5,33	7,37	11,88
Essen	14,55%	29,87%	48,37%	1,02	2,09	3,39
Freiburg	23,00%	4,66%	16,46%	5,29	1,07	3,79
Hanover	16,41%	24,97%	47,06%	3,12	4,74	8,94
Heidelberg	11,91%	0,31%	17,29%	3,10	0,08	4,49
Munich	22,10%	41,64%	60,26%	3,98	7,50	10,85
Münster	-4,19%	-16,24%	-1,17%	-1,64	-6,33	-0,46

Modal share changes are calculated according to Equations 7 and 8, using estimated bicycle ridership changes from Table 4, mobility changes from Table 5, and original modal share values from Table 1.

The results show that the modal share of cycling increased in all cities of the sample, except for Münster. The city of Münster is generally considered as a classic *bicycle city* and has a very high modal share of cycling. Thus, many trips were always by bike. During the pandemic, bicycle ridership decreases slightly more than overall mobility, thus resulting in a negative change in the modal share of cycling. 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. This change was especially pronounced in cities with a relatively lower modal share of cycling, with the highest modal share increases being in Bonn, Berlin, and Düsseldorf. As a consequence of the reduction in overall mobility, the modal share of cycling rose even in cities where no significant increases in the number of counted bicycles could be observed.

Moreover, the results show that the increases were greater under stricter government interventions. This implies that stricter government interventions had 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.

V. Conclusion

The Covid-19 pandemic affects individuals in many ways, including their mobility behavior. In this paper, we focus on the impact of the Covid-19 pandemic and subsequent government interventions on active mobility in 10 German cities during the first wave of the pandemic. For this purpose, we use data from automated pedestrian and bicycle-counting stations, as well as information on weather conditions and calendar events. By so doing, we can estimate the isolated impact of the Covid-19 pandemic on active travel. Moreover, we provide information on how the severity of government intervention impacts on active travel. We differentiate between the effects during the pandemic when no government interventions were in effect, when either business closures or contact restrictions were in effect, or when both business closures and contact restrictions were in effect.

We find that pedestrian levels in pedestrian zones decrease with higher local incidence values, and more government interventions lead 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, and increases in cities with a relatively low modal share of cycling. 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 and bicycle ridership, we estimate changes in the modal share of cycling. Except for Münster, 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.

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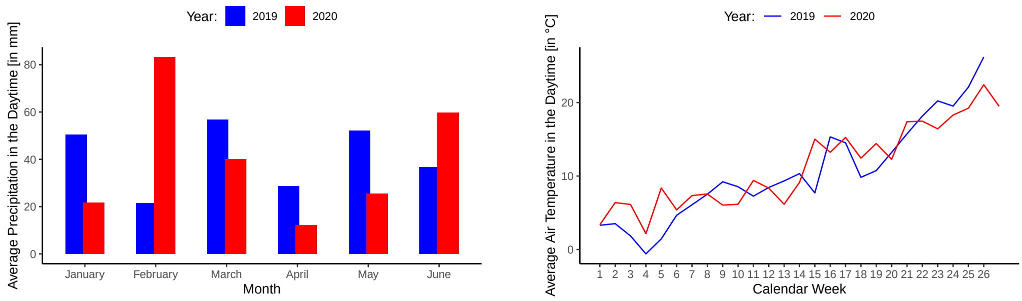
Appendices

A. Appendix

A. Weather Differences Between 2019 and 2020



(a) Precipitation (b) Air temperature

Figure 7. : Average weather conditions in the cities of our sample for 2019 and 2020

B. Government interventions in Cities of the Sample

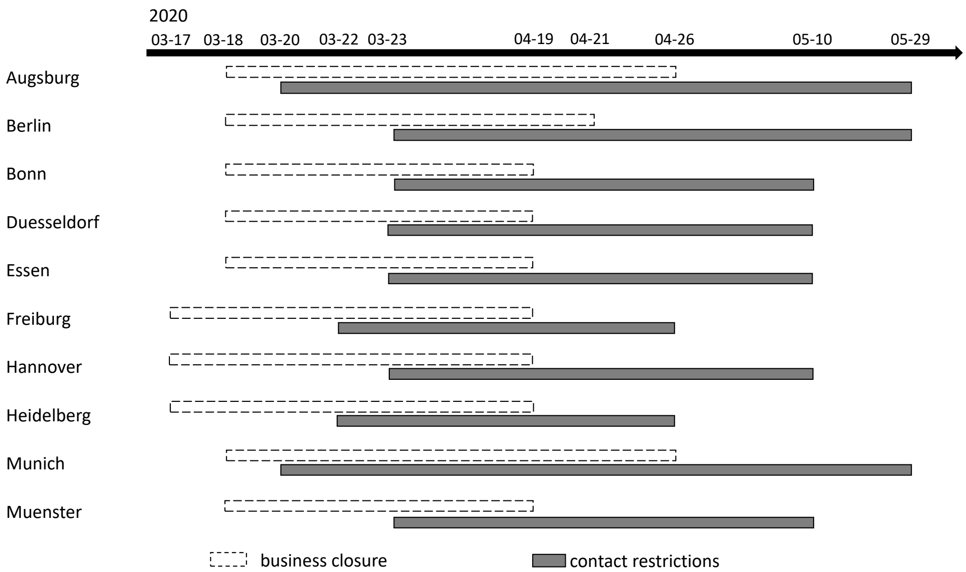
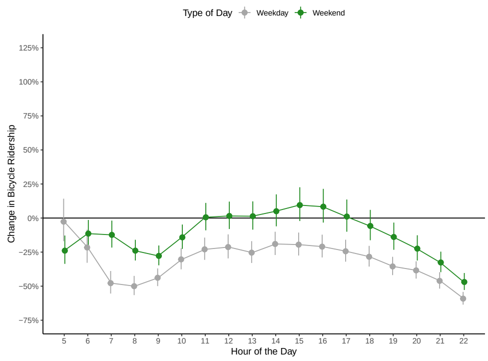
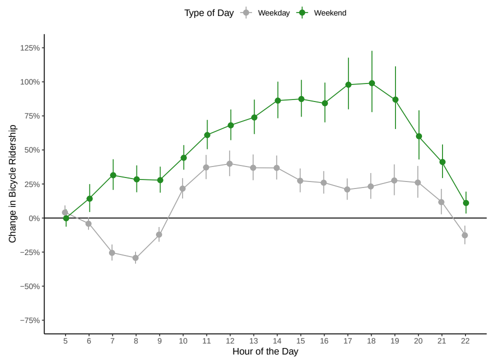


Figure 8. : Government interventions in Cities of the Sample

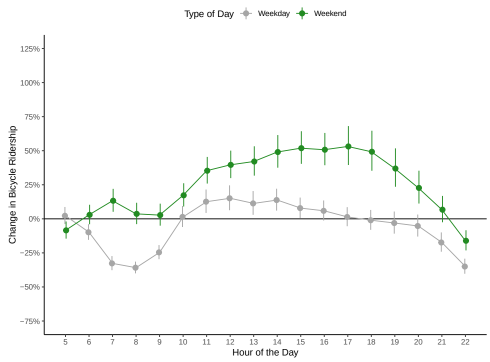
C. Hourly Impacts for Various Subsamples



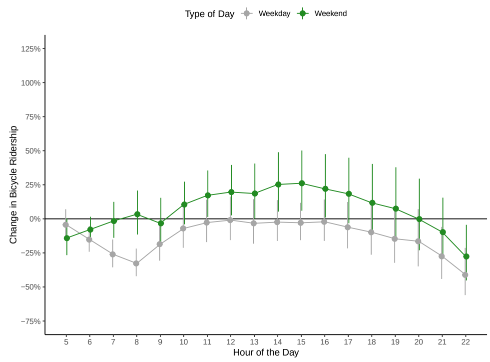
(a) Point Estimates of Hourly Covid-19 Pandemic Impact (Freiburg, Heidelberg, Münster)



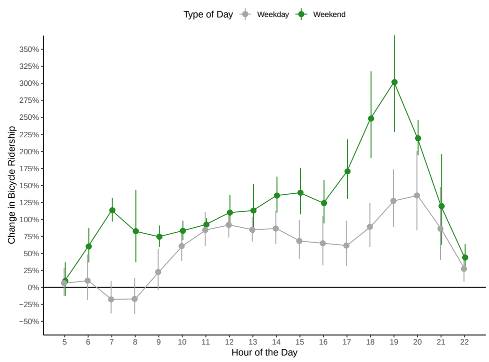
(b) Point Estimates of Hourly Covid-19 Pandemic Impact (Berlin, Bonn, Düsseldorf)



(c) Point Estimates of Hourly Covid-19 Pandemic Impact (Utilitarian Counters)



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



(e) Point Estimates of Hourly Covid-19 Pandemic Impact (Recreational Counters)

Figure 9. : Heterogeneity of Point Estimates of Hourly Covid-19 Pandemic Impact on Cycling

REFERENCES

Aultman-Hall, L., Lane, D., and Lambert, R. R. (2009). Assessing impact of weather and season on pedestrian traffic volumes. *Transportation Research Record*, 2140(1):35–43.

Beck, M. J. and Hensher, D. A. (2020a). Insights into the impact of covid-19 on household travel and activities in australia – the early days of easing restrictions. *Transport Policy*, 99:95 – 119.

Beck, M. J. and Hensher, D. A. (2020b). Insights into the impact of covid-19 on household travel and activities in australia – the early days under restrictions. *Transport Policy*, 96:76–93.

Böcker, L., Dijst, M., and Faber, J. (2016). Weather, transport mode choices and emotional travel experiences. *Transportation Research Part A: Policy and Practice*, 94:360–373.

Borkowski, P., Jażdżewska-Gutta, M., and Szmelter-Jarosz, A. (2021). Lockdowned: Everyday mobility changes in response to covid-19. *Journal of Transport Geography*, 90:102906.

Bucsky, P. (2020). Modal share changes due to covid-19: The case of budapest. *Transportation Research Interdisciplinary Perspectives*, 8:100141.

de Haas, M., Faber, R., and Hamersma, M. (2020). How covid-19 and the dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the netherlands. *Transportation Research Interdisciplinary Perspectives*, 6:100150.

Ermagun, A., Lindsey, G., and Loh, T. H. (2018). Urban trails and demand response to weather variations. *Transportation Research Part D: Transport and Environment*, 63:404 – 420.

Gkiotsalitis, K. and Cats, O. (2020). Public transport planning adaption under the covid-19 pandemic crisis: literature review of research needs and directions. *Transport Reviews*, pages 1–19.

Goldmann, K. and Wessel, J. (2020). Some people feel the rain, others just get wet: An analysis of regional differences in the effects of weather on cycling. *Research in Transportation Business & Management*, page 100541.

Kraus, S. and Koch, N. (2021). Provisional covid-19 infrastructure induces large, rapid increases in cycling. *Proceedings of the National Academy of Sciences*, 118(15).

Liu, C., Susilo, Y. O., and Karlström, A. (2014). Examining the impact of weather variability on non-commuters' daily activity–travel patterns in different regions of sweden. *Journal of Transport Geography*, 39:36 – 48.

Liu, C., Susilo, Y. O., and Karlström, A. (2015). The influence of weather characteristics variability on individual's travel mode choice in different seasons and regions in sweden. *Transport Policy*, 41:147 – 158.

Miranda-Moreno, L. F. and Nosal, T. (2011). Weather Or Not To Cycle: Temporal Trends and Impact of Weather on Cycling in an Urban Environment. *Transportation Research Record*, (2247):42–52.

Nurse, A. and Dunning, R. (2020). Is covid-19 a turning point for active travel in cities? *Cities & Health*, 0(0):1–3.

Santos, G., Maoh, H., Potoglou, D., and von Brunn, T. (2013). Factors influencing modal split of commuting journeys in medium-size european cities. *Journal of Transport Geography*, 30:127–137.

Schilling, J., Lehfeld, A.-S., Schumacher, D., Diercke, M., Buda, S., Haas, W., and Group, R. C.-. S. (2021). Disease severity of the first covid-19 wave in germany using reporting data from the national notification system.

Schlosser, F., Maier, B. F., Jack, O., Hinrichs, D., Zachariae, A., and Brockmann, D. (2020). Covid-19 lockdown induces disease-mitigating structural changes in mobility networks. *Proceedings of the National Academy of Sciences*, 117(52):32883–32890.

Shakibaei, S., de Jong, G. C., Alpkökin, P., and Rashidi, T. H. (2020). Impact of the covid-19 pandemic on travel behavior in istanbul: A panel data analysis. *Sustainable Cities and Society*, page 102619.

Teixeira, J. F. and Lopes, M. (2020). The link between bike sharing and subway use during the covid-19 pandemic: The case-study of new york's citi bike. *Transportation Research Interdisciplinary Perspectives*, 6:100166.

Wessel, J. (2020). Using weather forecasts to forecast whether bikes are used. *Transportation Research Part A: Policy and Practice*, 138:537 – 559.

Zhang, Y. and Fricker, J. D. (2021). Quantifying the impact of covid-19 on non-motorized transportation: A bayesian structural time series model. *Transport Policy*, 103:11–20.

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