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THE BENEFITS OF REMOTENESS - DIGITAL MOBILITY DATA, REGIONAL ROAD INFRASTRUCTURE, AND COVID-19 INFECTIONS

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The Benefits of Remoteness - Digital Mobility Data, Regional Road Infrastructure, and COVID-19 Infections*

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Abstract. We investigate the regional distribution of the COVID-19 outbreak in Germany. We use a novel digital mobility dataset, that traces the undertaken trips on Easter Sunday 2020 and instrument them with regional accessibility as measured by the regional road infrastructure of Germany's 401 NUTS III regions. We identify a robust negative association between the number of infected cases per capita and accessibility by road infrastructure, measured by the average travel time to the next major urban center. What has been a hinderance for economic performance in good economic times, appears to be a benevolent factor in the COVID-19 pandemic: bad road infrastructure. Using road infrastructure as an instrument for mobility reductions we assess the causal effect of mobility reduction on infections. The study shows that keeping mobility of people low is a main factor to reduce infections. Aggregating over all regions, our results suggest that there would have been about 63,000 infections less on May 5th, 2020, if mobility at the onset of the disease were 10 percent lower.

Keywords: Digital technology, Mobility data, Regional road infrastructure, Germany, COVID-19.

JEL: R11, R12, I18.

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1. Introduction

COVID-19 is a pandemic of immense dimension, bringing social and economic disruptions worldwide. An array of research papers emerged in the economics literature within a relatively short amount of time. This literature is mainly concerned with the impact that COVID-19 has on different sectors, regions, and countries in terms of economic and societal implications.

With our study we go another way. We address regional factors that are related to the differentiated spread of the disease in Germany. Specifically, we focus on the regional accessibility of NUTS III regions (*Kreise and kreisfreie Staedte*) through road infrastructure measuring the average travel time on roads towards the next major urban center (*Oberzentrum*). Since most regions do not contain a major urban center, the metric assesses both the quality of the network of regional roads as well as the connectivity with the next population hub. We argue that the accessibility measure is an interesting explanatory variable for the spread of COVID-19 as an instrument for mobility as well as in its own right (in reduced form).

In reduced-form regressions we show that there is a "benefit of remoteness": If roads are bad or absent it takes more time to visit distant relatives and friends, a feature, which naturally leads to more social distancing already without the implementation of lockdown policies. Inferior road infrastructure, which has been shown to be an impediment to regional development in "normal" times (Krenz, 2019a, 2019b), thus turns out to be beneficial in times of a pandemic because it prevents or reduces social interaction, in particular with people from other areas.

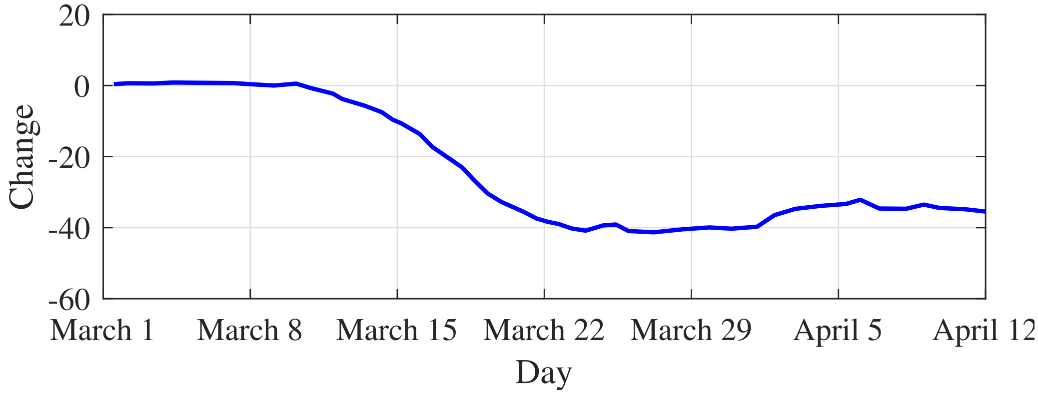
Mobility has been regarded as a key variable in the spread of the COVID-19 pandemic. Several German newspapers as well as the Robert Koch Institute, the leading German health institution in the fight against the disease, publish mobility data, gleaned from mobil phone users. The data are used to assess how well the population obeys social distancing policies. Mobility, however, is problematic as an explanatory variable for the spread of the disease because it is certainly endogenous and measured with error. Reverse causality could be an issue when people reduce mobility if the stock of infections and thus the probability to become infected increases. There are also myriads of channels conceivable that may cause omitted variable bias.

For road infrastructure, in contrast, we are convinced that it matters for the spread of a disease only because it alleviates mobility. In particular, it is not the mere presence of roads that allows the virus to travel from place to place but the fact that (potentially infected) people use roads to get in touch with other (potentially infected) people, an activity that we measure as mobility. In our regressions, due to data availability, we consider road infrastructure from 2018, which is certainly exogenous to the spread of COVID-19 but at the same time highly correlated with current infrastructure due to long times to build and low depreciation rates. The fact that road infrastructure changes only very slowly over time explains also our confinement on cross-sectional regressions.

The cross-sectional approach implies that we assess mobility on a particular point of time and here we take Easter Sunday. Easter Sunday, celebrated on April 12th in 2020, happened well after the closing of schools and the ban of big sports events on March 13 and after the shutdown of non-essential shops, hotels, restaurants, and other service providers and the ban of public gatherings of more than two people, on March 22nd in Germany. However, unlike in other European countries, the German federal government never ordered their citizens to stay at home. Some of the federal governments, in particular those with Southern borders (Bavaria, Saarland, Baden-Wuerttemberg, Rhineland-Palatinate) implemented stricter policies of social distancing with the most drastic measures, which came close to a curfew, in Bavaria. Nevertheless many politicians as well as scientists were afraid of compliance in particular around Easter were Germans are used to visit friends and relatives and to go on short-term holidays. Since also the weather stations predicted sunny and pleasant weather around 20 degrees for basically all German regions on Easter 2020, many politicians, among them chancellor Angela Merkel, were alarmed and admonished their citizens in several speeches on Holy Thursday to comply to the social distancing rules (e.g. Der Tagesspiegel, 2020).

As mobility measure we source data provided by the Robert Koch Institute and Humboldt University Berlin (Mobility Monitor, 2020a), which is gathered from mobile phone data. The data provides for each of the 401 German NUTS III regions the number of trips per day, measured relative to the average number of daily trips in the same month of the previous year. Figure 1, gleaned from the data in Mobility Monitor (2020b), shows the smoothed average change of mobility in Germany (compared to March 2019). We see that mobility declined by up to 40 percent and that most of the decline happened after enactment of the first set of policy measures on March 13 and before enactment of the second (more drastic) set of policy measures on March 22. Since the end of March, mobility is mildly on the rise again. The fact that the greatest increase of new COVID-19 cases happened from early to mid March, 2020 (RKI, 2020a) suggests that at least part of the mobility reduction is an endogenous response to increasing and/or high infection rates. Maloney and Taskin (2020) show that for the U.S. and other countries, mobility is strongly negatively associated with lagged COVID-19 cases, controlling for policy measures (non-pharmaceutical interventions) and interpret these results as a causal effect of infections on mobility.

Figure 1. Change in Mobility in Germany



Change of mobility compared to March 2019, 7 day moving averages. Source: Mobility Monitor (2020b).

In order to assess the causal effect of mobility on infections, we exploit the fact that there is large variation in mobility reductions across the German regions. Large mobility reductions are found in regions with good road infrastructure because people stayed at home on Easter 2020 and did not travel and move as much as they did in April 2019 (e.g. in Bavaria). On the other hand, mobility reductions are low in regions with bad road infrastructure because travel behaviour on Easter 2020 was not much different from traveling in 2019 due to remoteness and the constant low opportunities to leave home and travel smoothly and quickly on road networks (e.g. in East German regions). Especially, a Sunday in remote, low quality road infrastructure areas is tough: busses might not go on Sundays or have much less frequency to go. In other words: the travel restrictions for Easter 2020 apparently did not change much in remote areas' population mobility but changed greatly in highly accessible regions.

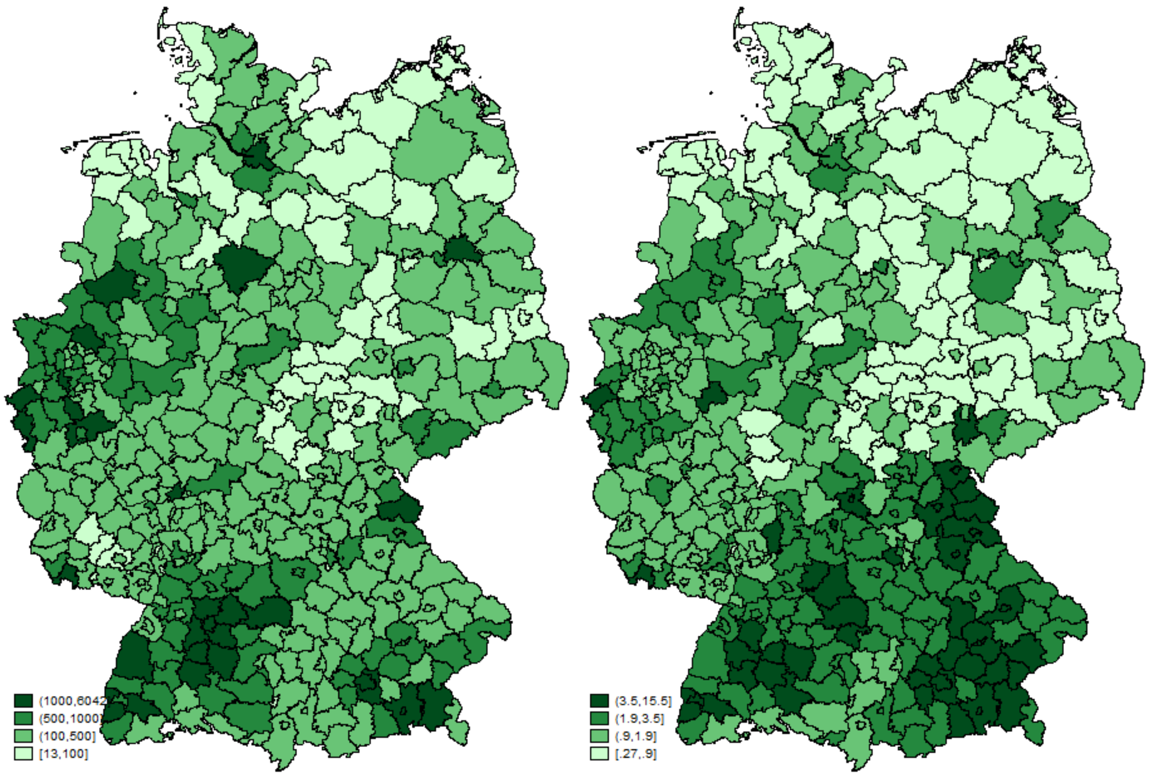
Our identification strategy assumes that road infrastructure affects the regional spread of COVID-19 infections only through its impact on the mobility of people. We instrument mobility reduction with regional road infrastructure and estimate the impact of (instrumented) mobility reduction on infections.

We are aware of one other study so far, which addresses the regional variation of COVID infections in Germany. Mense and Michelsen (2020) show that the number of newly infected cases significantly depends on the population density per region, on commuter flows and on rain days. Our study differs by focussing on the regional distribution of the stock of infected cases per capita and by using regional road infrastructure as instrument for mobility in order to make causal inferences. Chiou and Tucker (2018) argue that access to high-speed broadband alleviates social distancing and work from home and show that people in U.S. regions with high-speed internet (and with high income) are more likely to comply to social-distancing directives. Kapoor et al. (2020) argue that people are less outgoing on rainy days and use (unexpected) rainfall in U.S. regions to assess the impact of social distancing on COVID-19 infections. Dehning et al. (2020) and Donsimoni et al. (2020) use epidemiological simulations to assess the impact of social distancing interventions in Germany and conclude that the official interventions were effective in curbing the spread of the disease (and, in case of Donsimoni et al.) necessary in stopping the growth of infections. Greenstone and Nikam (2020) use an epidemiological model to estimate the (huge) monetary benefit from social distancing that accrues through avoided deaths.

2. Data

The Robert Koch Institute provides data on COVID-19 infection cases and death tolls down to the level of NUTS III regions which are the German 401 district-free cities and districts (*Kreise und kreisfreie Staedte*). We extract data on the total number of cases per region and on the number of cases per 1000 inhabitants. The data are from May 5th, 2020, 23 days after Easter Sunday. This ensures that time passed by regarding the incubation time, doctor's visits, testing and getting test results. Figure 2 displays in Panel A the total number of COVID-19 infections. It shows main hubs of infectious activity, like the region Heinsberg in the very West, several regions in the South-West, South, and in city areas, like Berlin, Munich, Hamburg, and Hannover. Panel B displays infections per capita (multiplied by a thousand). The map shows that many regions in East Germany have low numbers of infections per capita, while Bavaria and Baden-Wuertemberg in the South and South-West have the most infections per capita. It also reveals that there is only a weak association between population density and infections per capita. In particular, some large cities such as Berlin and Hannover display comparatively low levels of infections per capita.

Figure 2. COVID-19 Infections – Regional Distribution in Germany



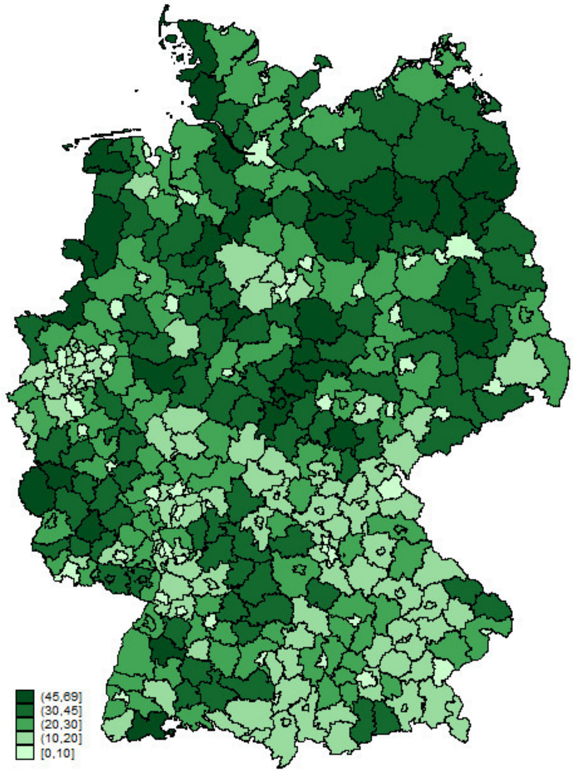
(A) COVID-19 infections, total

(B) COVID-19 infections per 1000 population

Note: The figure shows the regional distribution of COVID-19 infections across the German NUTS III regions (district-free cities and districts). Data as of May, 5th, 2020 from RKI (2020a).

Our main explanatory variable is the accessibility of regions by means of road infrastructure (*Erreichbarkeit von Oberzentren*) which is the average travel time by car (in minutes) from all communities of a NUTS III region to the next major urban center. These data are obtained from the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR, 2020) through its INKAR database (Indicators and Maps for Spatial and Urban Development). Major urban centers (*Oberzentren*) are agglomerations of the highest level of centrality. They are classified by functionality. In contrast to smaller agglomeration centers (*Mittel- and Unterzentren*) they provide services and infrastructure that satisfy non-essential and non-periodic needs such as theaters, museums, universities, special clinics, special shopping centers, and administration centers. Usually, larger cities are classified as major urban center. Germany consists of 401 NUTS III regions and by definition of the BBSR of 85 major urban centers (*Oberzentren*). Notice that, by construction, the accessibility indicator is lowest (namely zero = best accessibility) for cities that are classified as major urban centers and the indicator

Figure 3. Accessibility by Road Infrastructure



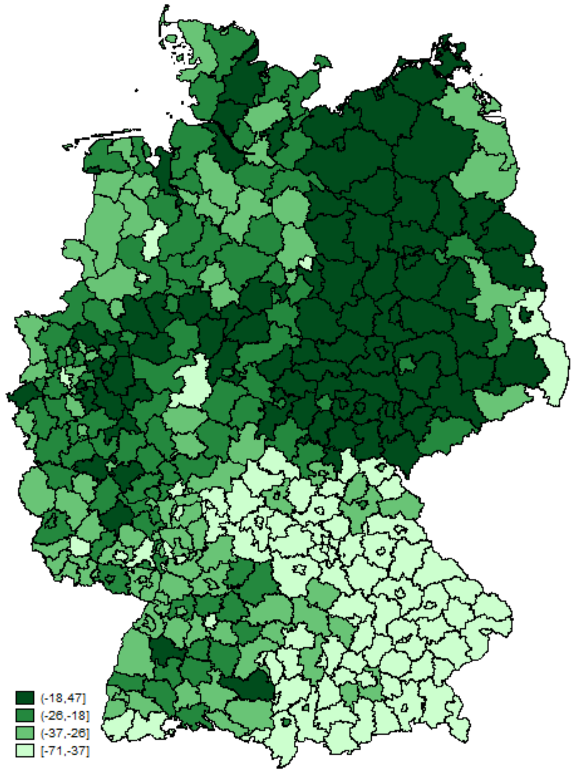
(A)

Note: The figure shows the regional distribution of accessibility on road infrastructure across the German NUTS III regions (district-free cities and districts), measured by travel time on roads (in minutes) to reach a major urban center. Darker colors reflect higher travel times. Data for the year 2018 from the BBSR (2020).

increases with remoteness of the region. Figure 3 displays the accessibility of the German NUTS III regions. It becomes apparent that especially in the East German regions, travel times are higher. Travel times on roads are lower in the South, especially in Bavaria.

As regional control variables we source from the INKAR data base information on outward job commuters in percent, the number of general practitioners (medical doctors) per 10000 population, and regional GDP per worker. We always use, for each explanatory variable, data from the latest available year, which, for example, is from the year 2018 for accessibility. Since these control variables are persistent characteristics of regions, values from the recent past are good proxies for the present. We corroborate this claim by computing the correlations between the latest available data and previous years' data in Table A.4. These correlations are very high, between 92 and 99 percent, strongly suggesting that past values are reliable proxies of a region's current performance. A description of the variables and sources can be found in Table

Figure 4. Change in Mobility



(A)

Note: The figure shows the regional distribution of changes in mobility on Easter Sunday 2020 across the German NUTS III regions (district-free cities and districts). Mobility change is defined as the percentage change in mobility for a chosen day (here Easter Sunday 2020) as compared to the mobility on an average Sunday in April 2019 (the previous year). Dark green colors reflect a small reduction or even an increase in the mobility rate; light green colors reflect a large reduction in the mobility rate. Data from Mobility Monitor (2020a) by Robert Koch Institute and Humboldt University Berlin.

A.1. Descriptive statistics are shown in Table A.2. Correlations between variables are shown in Table A.3.

To measure mobility we use a novel dataset collected by the Robert Koch Institute and Humboldt University Berlin (Mobility Monitor, 2020a). From the Mobility Monitor website we extracted data on mobility profiles of individuals from the German NUTS III regions for Easter Sunday 2020 across the 401 NUTS III regions. The Mobility Monitor website displays in an online monitor 'how much more or less are people on the go', that is the change in trip frequency as compared to an average day of the same month in the year 2019. The mobility data are constructed from mobile phone data and make use of the information on the number of trips within and between areas (NUTS III regions) but do not trace single individuals and their movements. This is important, as every institution in the process of the data generation and aggregation process guarantees full anonymity. According to Mobility Monitor (2020a), "a movement is registered by the mobile phone provider when an individual switches cell tower areas, and ends when the person becomes stationary again. The start- and end-tower can be the same." The data they use comes from the German Telekom and from Telefonica and is provided by the firms Teralytics and Motionlogic.

Figure 4 displays the change in mobility for Easter Sunday 2020 as compared to an average Sunday in April 2019. As can be seen, the highest reductions in mobility as compared to the previous year (light green colours) took place in the South German regions, especially in Bavaria. The smallest reductions or even small increases in mobility took place in the East German regions.

In Table A.6 we collect the top 10 of the German regions regarding i) the highest number of total COVID-19 infections, ii) the highest numbers of infections per capita, iii) the largest decreases in mobility between Easter 2020 and April 2019, and iv) regions with high accessibility (few minutes of travel time). It becomes apparent that the regions with the highest numbers of infection cases per capita are located in the South, in Bavaria (BY) especially. Mobility reductions are also largest (more negative value) in various regions of Bavaria. In Table A.7 we present the bottom 10 regions according to the same criteria, but with lowest mobility reductions and the worst road accessibility. The ranking shows that the number of cases per capita is especially low for some East German regions, located in the federal states of Sachsen-Anhalt (SA), Brandenburg (BB), and Mecklenburg-Vorpommern (MV), as well as for regions in Northern Germany, located in Schleswig-Holstein (SH) and Niedersachsen (N). Likewise, the lowest values for mobility reductions and the worst accessibility by road infrastructure are also found in the East and the North of Germany.

3. Empirical Analysis

3.1. **The Benefit of Remoteness.** We first run a regression of the impact of road infrastructure (accessibility) on the log of the number of infected cases per capita (times 1000). The regression equation is given by

$$\log(Cases - per - capita)_r = \beta_0 + \beta_1 Accessibility_r + \mathbf{X}_r \beta_2 + \theta_i + \epsilon_r \tag{1}$$

where r is the NUTS III region, $\mathbf{X}$ is a vector of explanatory factors including job commuters as a share of employees, general practitioners per population, GDP per worker, and metropolitan area, θ are regional fixed effects, and ϵ is an idiosyncratic error term.

The results are shown in Table 1. In the first column, infection cases are regressed only on accessibility. We see a negative relationship that is statistically highly significant. A larger degree of remoteness per NUTS III region by 1 more minute travel time on roads to reach a major urban center is associated with a decrease in the number of per-capita infections by about 1.18 percent. In column 2 we add further explanatory variables at NUTS III level. We see an increase in the coefficient for accessibility (in absolute terms) of up to -1.66 percent. Per capita infections are significantly positively associated with the share of job commuters (therewith supporting evidence from Mense and Michelsen, 2020), as well as with regional GDP and general practitioners.

Table 1. The Impact of Accessibility by Road Infrastructure on COVID-19 Cases in Germany

	(1)	(2)	(3)	(4)	(5)
Dependent variable: log(Cases-per-capita)					
Accessibility	-0.0118***	-0.0166***	-0.0166***	-0.0085***	-0.0056**
	(0.0022)	(0.0025)	(0.0025)	(0.0022)	(0.0022)
GDP		0.0133***	0.0131***	0.0003	-0.0002
		(0.0025)	(0.0024)	(0.0026)	(0.0026)
Medical doc		0.1078***	0.1113***	-0.008	-0.0624
		(0.0401)	(0.041)	(0.0345)	(0.0417)
Job commuters		0.0135***	0.0138***	0.0062***	0.0041**
		(0.0021)	(0.0022)	(0.0020)	(0.0020)
Metropolitan area			0.1269	0.0579	0.1416
			(0.1278)	(0.1457)	(0.1521)
Laboratory tests				0.1759***	0.0897***
				(0.0132)	(0.021)
Regional Fixed Effects	no	no	no	no	yes
Number of observations	401	401	401	401	401
R^2	0.070	0.205	0.206	0.458	0.504

Note: The table displays estimates for the impact of regional road infrastructure (accessibility) on infected cases in Germany. The dependent variable is the logarithm of the number of infected COVID-19 cases per capita. The regional level of the analysis is the district-free cities and districts (NUTS III regions) in Germany. Data sources: Robert Koch Institute, INKAR/ BBSR. Robust standard errors were computed and are displayed in parentheses. *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, * denotes significance at the 10 percent level.

In column (3) we add a dummy for metropolitan area (defined as the 10 largest cities in Germany according to population size). We see that, controlling for accessibility and other confounders, metropolitan areas contribute insignificantly to infections per capita. In column (4) we add the percentage of positive results from laboratory tests, a statistic, which is available at the state (*Bundesland*) level. See Table A.5 for a list of testing levels, and the share of positive tests. As can be seen, the size of all confounders and the coefficients of regional GDP and medical docs become statistically insignificant. The coefficient of medical docs switches sign, indicating that the previous positive association with infections (in specification 2 and 3) took up the impact of laboratory tests. Most importantly, the coefficient on accessibility remains significantly negative, albeit of smaller size. Including further fixed effects at the level of regions of North, North-West, North-East, West, South-East and South (South Germany as reference category) further reduces the coefficient of accessibility but it remains statically significant and negative (-0.0057, and p-value of 0.012). According to the point estimate of specification (6), 1 more minute travel time on roads to reach a major urban center is associated with a decrease in the number of per-capita infections by about 0.57 percent. This means that a one standard deviation increase in remoteness explains a 9 percent lower level of infections per capita.

3.2. **The Effect of Mobility Reduction on Infections.** To identify the effect of mobility on the number of infected COVID-19 cases, we follow the strategy outlined in Section 1. We use the accessibility measure, i.e. the travel time on road infrastructure to reach a major urban center to instrument for changes in mobility on Easter Sunday 2020, compared to an average Sunday in April 2019, denoted by $\Delta Mobility$. For the IV regressions, we estimate the following equations:

$$log(Cases - per - capita)_r = \gamma_0 + \gamma_1 \Delta \widehat{Mobility}_r + \mathbf{X}_r \gamma_2 + \theta_i + \epsilon_r \tag{2}$$

$$\Delta Mobility_r = \delta_0 + \delta_1 Accessibility_r + \mathbf{X}_r \delta_2 + \theta_i + \eta_r. \tag{3}$$

The results are shown in Table 2, along with simple OLS regressions of the log of infected cases per capita on mobility. The results in columns 1 to 5 suggest a negative association between the change of mobility and infections, which is robust to the addition of potential confounders (regional GDP, general practitioners, job commuters, a metropolitan dummy, laboratory tests and regional fixed effects). The results suggest that, ceteris paribus, the regions with the greatest reduction of mobility on Easter Sunday have accumulated the largest number of infections. The intuition for this result is straightforward. In regions where mobility reduction is greatest, mobility was greatest before the reduction and thus contributed to a faster spread of the disease and a higher stock of infections as of May 2020. However, the results in columns 1 to 5 regarding the mobility measure have to be interpreted carefully since, as argued in the Introduction, mobility is likely an endogenous regressor.

Table 2. The Impact of Mobility on COVID-19 Cases in Germany

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Log(Cases-per-capita)							
	OLS	OLS	OLS	OLS	OLS	First Stage	IV
Δ Mobility	-0.0245***	-0.0224***	-0.0223***	-0.0107***	-0.0071***		-0.0384**
	(0.0022)	(0.0024)	(0.0024)	(0.0023)	(0.0026)		(0.0193)
Accessibility						0.1469***	
						(0.049)	
GDP		0.0088***	0.0088***	0.0002	0.0004	-0.0126	-0.0007
		(0.0023)	(0.0023)	(0.0022)	(0.0023)	(0.0567)	(0.0024)
Medical doc		0.0012	0.0022	-0.0462	-0.0769*	-0.8061	-0.0934*
		(0.0419)	(0.0428)	(0.036)	(0.0421)	(0.7797)	(0.0495)
Job commuters		0.0056***	0.0057***	0.0025	0.0018	0.0015	0.0042*
		(0.0017)	(0.0018)	(0.0017)	(0.0017)	(0.0393)	(0.0022)
Metropolitan area			0.0350	0.0251	0.0977	-7.2473***	-0.137
			(0.1109)	(0.1309)	(0.1457)	(2.5863)	(0.2125)
Laboratory tests				0.1552***	0.0859***	-0.5166	0.0698***
				(0.0147)	(0.0203)	(0.4528)	(0.0266)
Regional Fixed Effects	no	no	no	no	yes	yes	yes
Number of observations	401	401	401	401	401	401	401
R^2	0.276	0.3090	0.3091	0.468	0.506	0.515	0.287
F-Stat						39.26	

Note: The table displays estimates for the impact of the change in mobility (instrumented by regional road infrastructure) on infected cases per capita in Germany. The dependent variable is the log of the number of infected COVID-19 cases per 1000 population. The regional level of the analysis are the district-free cities and districts (NUTS III regions) in Germany. Data sources: Mobility Monitor, Robert Koch Institute, Humboldt University Berlin, INKAR/ BBSR. Robust standard errors were computed and are displayed in parentheses. *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, * denotes significance at the 10 percent level.

Results from the first stage regressions of mobility on accessibility via road infrastructure are shown in column (6) of Table 2. We obtain a significantly positive effect of accessibility and the F-statistic of 39.26 indicates a strong instrumental variable. For the intuition it helps to recall the metric of these variables. According to the point estimate, an increase of travel time to the next urban center by 1 minute explains a 0.15 percent increase of Δ mobility. In other words, a 1 minute reduction in travel time explains a 0.15 decline of the mobility change (a larger mobility reduction) on Easter Sunday 2020 (compared to 2019). Of the included potential confounders, only metropolitan area exerts a statistically significant influence on mobility. Intuitively, it makes sense that mobility reduction is higher in metropolitan areas because pre-disease mobility was higher (having access to busses, subways, roads, etc.). It also agrees with our intuition that medical docs, job commuters, and laboratory tests do not influence mobility. However, it could be argued that regional GDP (from 2017) may have a (mild) impact on regional road infrastructure (from 2018) and that the disease may spread faster among poorer individuals, implying that it would be more prevalent in poorer regions. It is thus important that we condition on regional GDP and shut down this potential backdoor path of causality. However, as seen in column (6), we do not find a significant impact of regional GDP on mobility.

The IV estimation results are shown in column (7). The mobility change significantly and negatively impacts the number of infected cases per capita. An increase in the change of mobility value by 1 percent (for Easter Sunday 2020 as compared to an average Sunday in April 2019) explains a decline in the number of infected cases per capita by 3.8 percent. Again, it is helpful to recall the metric of the variables and that mobility declined by more in the well-connected regions where pre-pandemic mobility was highest. The results thus indicate that infections would have been by 3.8 percent higher if mobility at the outbreak of the pandemic would have been 1 percent higher than it actually was. Or, in other words, if the pre-pandemic mobility in a region was one standard deviation larger, infections per capita would have been 58 percent higher.

The mobility coefficient in the IV regressions is substantially larger than the coefficient in OLS regressions. This feature indicates that reverse causality is not the greatest cause of bias in the OLS regressions. Aside from measurement error, the OLS estimate is biased downward by omitted variables that either affect mobility positively and infections negatively, or vice versa. It is easy to imagine omitted variables of this kind (like the availability of masks). The IV approach overcomes this problem and suggests a large effect of mobility on infections. Of the included confounders, laboratory tests remain strongly positively associated with infections and medical docs and job commuters remain (weakly) significant with the expected signs (the p-value for job commuters is 0.061).

Table 3. Simulations: Effects of a 1 Percent Pre-Disease Mobility Reduction on Infections

	(1) Cases	(2) Population	(3) Cases per 1000	(4) 3.84 percent decrease	(5) New cases per 1000	(6) Counterfactual total cases	(7) Counterfactual reduction of cases
Berlin	6042	3754418	1.6093	0.0618	1.5475	5810	232
Cologne	2323	1085664	2.1397	0.0822	2.0575	2234	89
Dresden	570	554649	1.0277	0.0395	0.9883	548	22
Ostallgaeu	489	140316	3.485	0.1338	3.3512	470	19
Goettingen	765	328074	2.3318	0.0895	2.2422	736	29
Hamburg	4644	1841179	2.5223	0.09686	2.4254	4466	178
Muenchen	5846	1471508	3.9728	0.1526	3.8202	5622	224
Rosenheim *Landkreis*	2081	260983	7.9737	0.3062	7.6675	2001	80

Note: The table shows the number of total cases, the size of the population, cases-per-1000 inhabitants, the impact of a 3.8 percent decline in the cases-per-1000 ratio, the resulting counterfactual cases-per-1000-inhabitants, the implied counterfactual number of total cases, and the counterfactual decline of infections.

In Table 3 we report results from simple calculations of the impact of mobility change on infections for selected German regions. For Berlin, for example, the regressions predict that if mobility at the onset of the disease were 1 percent lower (such that the mobility reduction on Easter Sunday 2020 were 1 percent weaker), then the number of COVID-19 infections would have been 5810 instead of 6042 on May, 5th, which means a decrease of 232 cases. An overview of the respective mobility and accessibility values is given in Table A.8 in the Appendix. In total, for entire Germany, the regressions predict that if mobility at the onset of the disease were 1 percent lower, then instead of the 163,860 cases as of May 5th 2020, there would have been 157568 cases in total, i.e. 6292 cases less. In other words, if mobility were 10 percent lower, there would have been 62,920 cases less.

4. Conclusion

In this paper, we analyzed the regional distribution of COVID-19 infections in Germany and the regional factors that explain its distribution. We made use of a novel, innovative digital technology dataset which traces mobility profiles of the inhabitants of the 401 German regions. Our analysis showed that COVID-19 infections are spread unevenly across regions. There exists a distinct divide between the East and North German regions - which show lower infection rates - and the West and South German regions with higher infection rates.

We showed that in times of pandemics there exists a benefit of remoteness. Controlling for potential confounders, regions that are far away from major urban centers (by means of travel time on roads) display less infections. In order to make inferences on the causal effect of mobility reductions on infections, we use road infrastructure as an instrument for the change of mobility (on Easter Sunday 2020 compared to an average Sunday in 2019). Our results show that not being very mobile is a benevolent factor for reducing COVID-19 infection rates. According to the IV regression results, 1 percent less mobility reduction, which means a one percent lower mobility level at the outbreak of the disease, explains a decline of infections by 3.8 percent. Reaching other people, urban centers or meeting points contributes to an increase in infection rates. Social distancing, here conceptualized as bad accessibility and mobility, appears to be a main factor to hold infection rates down.

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Appendix

Table A.1. Description of variables

Variable	Description and Measurement	Data
Cases	Infected COVID-19 cases as of 5.5.2020, per NUTS III region, total	Robert Koch Institute
Cases-per-pop	Infected COVID-19 cases per 1000 population as of 5.5.2020, per NUTS III region, logged measure	Robert Koch Institute
Digital Mobility Data	Percentage change of trips undertaken on Easter Sunday (12.4.2020) compared to average Sunday in April in 2019, at NUTS III level	COVID-19 Mobility Monitor by Robert Koch Institute and Humboldt University Berlin, data distributed and analyzed by Teralytics and Motionlogic
Accessibility (*Erreichbarkeit von Oberzentren*)	Average travel time from all communities of the NUTS III region by car to next agglomeration centre, in minutes, 2018	INKAR / BBSR based on *Erreichbarkeitsmodell by BBSR*
GDP	GDP per worker in thousand euros, in NUTS III region, 2017	INKAR / BBSR based on *Arbeitskreis Volkswirtschaftliche Gesamtrechnung der Laender*, Eurostat Regio Database
Medical doc	General pratitioners per 10000 population (*Allgemeinarzt*), in NUTS III region, 2017	INKAR / BBSR based on *Kassenaerztliche Bundesvereinigung*
Job commuters	Job commuters (outward) as a share to social security related employees at place of living, in percent, in NUTS III region, 2017	INKAR / BBSR based on *Pendlermatrizen der Bundesagentur fuer Arbeit*
Metropolitan area	The 10 largest German cities according to their population size, i.e. Berlin, Hamburg, Munich, Cologne, Frankfurt am Main, Stuttgart, Duesseldorf, Leipzig, Dortmund, Essen	Regional Database GENESIS
Laboratory tests	Positive Corona test results per *Bundesland*, in percent	Robert Koch Institute

Table A.2. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Obs.
Cases	408.6284	570.7205	13	6042	401
Cases-per-pop	1.994804	1.565289	.2789	15.4336	401
Digital Mobility Data	-26.07481	15.34322	-71	47	401
Accessibility	22.56359	16.03361	0	69	401
GDP	69.25614	12.07636	51.83299	163.5925	401
Medical doc	4.180509	.7015702	2.042603	6.210037	401
Job commuters	64.0552	16.72825	13.88321	88.59399	401
Metropolitan area	0.0249	0.1561	0	1	401
Laboratory tests	6.7768	2.4075	1.9	10.7	401

Table A.3. Correlation Matrix

	Cases	Cases-per-pop	GDP	Med doc	Commuters	Mobility	Metropol	Laboratory
Cases-per-pop	0.3749							
GDP	0.3056	0.1737						
Med doc	-0.1801	0.0539	-0.2093					
Commuters	-0.1622	0.1096	-0.0879	0.1378				
Mobility	-0.1589	-0.4165	-0.3015	-0.1387	-0.0080			
Metropol	0.5757	-0.0067	0.2070	-0.1951	-0.3267	-0.0754		
Laboratory	0.2538	0.5061	0.3896	0.1188	0.1341	-0.5767	0.0328	
Accessibility	-0.2060	-0.1772	-0.2856	0.1274	0.5047	0.3193	-0.2253	-0.2388

Table A.4. Correlation Matrix – Check for Persistence

	Accessibility 2018	GDP 2017	Commuters 2017	Med doc 2017
Accessibility 2012	0.9210			
GDP 2016		0.9907		
Commuters 2016			0.9997	
Med doc 2016				0.9781

Table A.5. Laboratory Tests on SARS-CoV-2 as of 6.5.2020

Bundesland	Total number	Number positive results	Number positive percent	Test share	Population share
Baden-Wuerttemberg	63.092	6.763	10.7	7.77	13.32
Bayern	203.636	17.180	8.4	25.09	15.73
Berlin	66.255	3.563	5.4	8.16	4.52
Brandenburg	13.033	582	4.5	1.61	3.02
Bremen	1.126	21	1.9	0.14	0.82
Hamburg	6.540	433	6.6	0.81	2.21
Hessen	34.021	3.193	9.4	4.19	7.54
Mecklenburg-Vorpommern	5.416	112	2.1	0.67	1.94
Niedersachsen	66.917	3.247	4.9	8.25	9.6
Nordrhein-Westfalen	234.069	15.917	6.8	28.84	21.57
Rheinland-Pfalz	45.520	3.045	6.7	5.61	4.91
Saarland	300	14	4.7	0.04	1.19
Sachsen	15.336	772	5.0	1.89	4.91
Sachsen-Anhalt	31.341	833	2.7	3.86	2.66
Schleswig-Holstein	10.923	366	3.4	1.35	3.48
Thueringen	14.037	475	3.4	1.73	2.58
unknown	144.454	12.965	9.0	-	-
Average	-	-	7.3	-	-
Total	956.016	69.481	7.3	100	100

Note: Data from the Robert Koch Institute (RKI, 2020c) and Regional Database GENESIS. Last two columns: computations by the authors. The percentage of positive tests displayed in the middle column is taken for regressions.

Table A.6. The 'Top 10' for Variables across Regions

	Cases	Cases per pop	Mobility	Accessibility
1	Berlin (B)	Tirschenreuth (BY)	Berchtesgadener Land (BY)	Wunsiedel i.F. (BY)
2	Muenchen (BY)	Wunsiedel i.Fg. (BY)	Lindau (BY)	RV Saarbruecken (S)
3	Hamburg (H)	Neustadt a.d.Waldn. (BY)	Bad Kissingen (BY)	Altoetting (BY)
4	Koeln (NW)	LK Rosenheim (BY)	Erding (BY)	Kulmbach (BY)
5	Rosenheim LK (BY)	Straubing (BY)	Garmisch Partenkirchen (BY)	Dillingen a.D (BY)
6	Hannover (N)	Rosenheim (BY)	Frankfurt Oder (BB)	Frankenthal Pf. (RP)
7	Aachen (NW)	Weiden i.d.OPf. (BY)	Ostallgaeu (BY)	Oberallgaeu (BY)
8	Heinsberg (NW)	Heinsberg (NW)	Regen (BY)	Herne (NW)
9	Esslingen (BW)	Traunstein (BY)	Rottal-Inn (BY)	Deggendorf (BY)
10	Ludwigsburg (BW)	Hohenlohekreis (BW)	Miesbach (BY)	Coburg (BY)

Note: The table displays the 10 NUTS III regions that have i) the highest values for the number of total COVID-19 cases, ii) the highest values for the number of COVID-19 cases per 1000 population, iii) the largest decreases in mobility as compared to April 2019, iv) the best regional accessibility which means a very low travel time in minutes to reach an urban center (excluding NUTS III regions that are classified as major urban center with zero travel time). Data sources: Mobility Monitor by Robert Koch Institute and Humboldt University Berlin, INKAR/ BBSR.

Table A.7. The 'Bottom 10' for Variables across Regions

	Cases	Cases per pop	Mobility	Accessibility
1	Suhl (TH)	Mansfeld-Suedh. (SA)	Brandenburg a.d.H. (BB)	Luechow D. (N)
2	Emden (N)	Wilhelmshaven (N)	Barnim (BB)	Stendal (SA)
3	Luechow D. (N)	Uckermark (BB)	Jerichower Land (SA)	Elbe-Elster (BB)
4	Eisenach (TH)	Rostock LK (MV)	Saalekreis (SA)	Dithmarschen (SH)
5	Wilhelmshaven (N)	Prignitz (BB)	Suhl (TH)	Prignitz (BB)
6	Prignitz (BB)	Ludwigslust-P. (MV)	Weimarer Land (TH)	Ostprignitz-R. (BB)
7	Hildburghausen (TH)	Ostholstein (SH)	Salzlandkreis (SA)	Uckermark (BB)
8	Wittmund (N)	Friesland (N)	Unstrut-H. K. (TH)	Aurich (N)
9	Frankfurt Oder (BB)	Emden (N)	Schwerin (MV)	G. Bentheim (N)
10	Pirmasens (RP)	Salzlandkreis (SA)	Emden (N))	Emsland (N)

Note: The table displays the 10 NUTS III regions that have i) the lowest values for the number of total COVID-19 cases, ii) the lowest values for the number of COVID-19 cases per 1000 population, iii) the lowest decreases, or even increases in mobility as compared to April 2019, iv) the worst regional accessibility which means a high travel time in minutes to reach an urban centre. Data sources: Mobility Monitor by Robert Koch Institute and Humboldt University Berlin, INKAR/ BBSR.

Table A.8. Mobility and Accessibility of Selected Regions

	Mobility	Accessibility
Berlin	-25	0
Cologne	-34	0
Dresden	-17	0
Ostallgaeu	-58	19
Goettingen	-19	25
Hamburg	-33	0
Muenchen	-48	0
Rosenheim *Landkreis*	-51	18
Jerichower Land	13	28
Ludwigslust-Parchim	-2	42
Magdeburg	-4	0

Note: The table shows mobility (the change in mobility between Easter Sunday 2020 and an average Sunday in April 2019, in percent) and accessibility (the travel time in minutes from all communities of a NUTS III region to reach the next major urban center) for selected regions.