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Breaks and Breakouts:
Explaining the Persistence of Covid-19

by

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Breaks and Breakouts:

Explaining the Persistence of Covid-19[†]

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Abstract

This paper investigates the role of large-outbreaks on the persistence of Covid-19 over time. Using data from 649 European regions in 14 countries, I first show that school-holiday-breaks in late February/early March 2020 (weeks 8, 9 and 10) led to large regional outbreaks of Covid-19 in the spring with the spread being 60% and up-to over 90% higher compared to regions with earlier breaks. While the impact of these initial large-outbreaks fades away over the summer months it systematically reappears from the fall as regions with school-breaks in weeks 8, 9 and 10 had 30-70% higher spread. This suggests that following a large-outbreak there is a strong element of underlying (latent) regional persistence of Covid-19. The strong degree of persistence highlights the *long-term* benefits of effective (initial) containment policies as once *a* large outbreak has occurred, Covid-19 persists. This result emphasizes the need for vaccinations against Covid-19 in regions that have experienced large outbreaks but are well below herd-immunity, to avoid a new wave of cases from the fall of 2021.

Keywords: Covid-19, pandemic, persistence, vaccination strategy, school-breaks

1 Introduction

In early March 2020, Europe became the center of the Covid-19 pandemic with the number of cases and deaths increasing exponentially. On March 11th the WHO declared Covid-19 a pandemic and containment measures intensified across Europe. Notable differences could however be seen both within and between similar countries. From figure 1 we can see how

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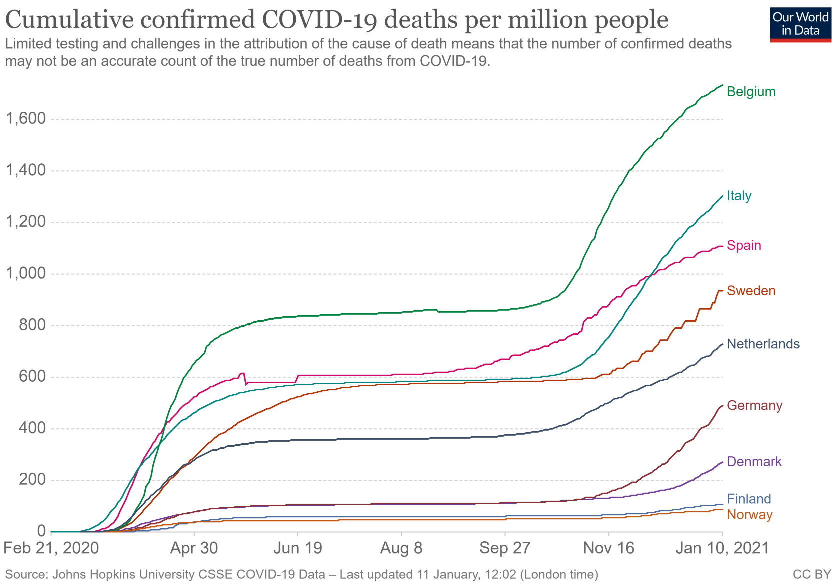


Figure 1: The cumulative number of confirmed Covid-19 deaths per capita in Europe (selected countries). *Source: Hasell et al. (2020)*

countries that had a relatively high number of deaths per capita in the spring are relatively hard hit from the fall. Hence, the patterns persist even after the summer holiday months when the spread of Covid-19 appeared minimal.

In this paper I contribute to the understanding of these patterns in the data.[1] The main contributions are twofold. First, as Covid-19 was only found in a limited number of places in Europe in mid-February human transportation was needed to distribute the virus to new places. I show that the clustered school-breaks during this critical period played a large role in the initial distribution of Covid-19.[2] Secondly, show how the impact of large initial outbreaks still persists in the fall/winter of 2020 even after various efforts to contain the spread of Covid-19. Hence, areas with high initial exposure (school-breaks in week number 9, 10 or 8) are consistently relatively worse hit in the fall and early winter 2020.

[1]A recent paper by Murray (2020) calls on the economic profession to contribute to the discussion on Covid-19. "*Indeed, the efforts of economists in tackling the economic sequelae of this pandemic are vitally needed, as are the development of tools for tracking, predicting, and preventing future pandemics based on understanding the flow of people, goods, and other economic activity around the globe.*" This paper is my contribution to that effort.

[2]It should be noted that independently and parallel to this work, Björk, Mattisson, and Ahlbom (2020) have used the variation in winter breaks to investigate policy effectiveness and the impact on excess deaths in the spring of 2020. This paper also complements phylogenetic analyses used to track the spread of the virus over space, such as, Lemieux et al. (2020), Gudbjartsson et al. (2020) and Bluhm et al. (2020).

2 Background

First cases of Covid-19 were identified in Europe in January 2020 and only sporadic cases reported until middle of February. From the WHO Covid-19 situation report on February 21st, only 47 cases had been confirmed in Europe and 1200 outside of China.[3] The situation escalated rapidly in Europe from this point, and on March 13th the Director-General of the World Health Organization noted that "*Europe has now become the epicenter of the pandemic, with more reported cases and deaths than the rest of the world combined, apart from China.*" Hence, in the short time-span from the 21st of February until the 13th of March Covid-19 took hold and spread uncontrolled throughout Europe.

During this pivotal period, in late February and early March, many European countries had school-breaks.[4] Anecdotal evidence from the initial inflow of cases in late February/early March could often be traced back to individuals traveling to ski-resorts in the Italian/Austrian alps or from other countries during these breaks.[5] Since school-breaks are generally either region-week or country-week specific they may lead to multiple simultaneous introductions of Covid-19. The geographic and week wise *clustering* of school-breaks increases therefore the likelihood of multiple simultaneous independent cases being introduced into a sub-national area upon return from travel during the holiday. This is significant as Kucharski et al. (2020) find that once at least four (ten) *independent* cases of Covid-19 have been introduced into a new location there is over 50% (90%) chance that a *large* outbreak will occur. This also underscores why school-breaks are potentially more significant for the initial exposure than business travel, which tends to be less clustered and clearly defined by both geography and time.

Before proceeding further it is useful to create a timeline for the spread of Covid-19 in Europe to pinpoint which weeks, were at the time, *thought* to have been safe for travel and which weeks, ex-post, are most likely related to high exposure. From figure 2 we can see that only a handful

[3] Over half of which were linked to the Diamond Princess cruse-ship.

[4] The generic term *school-breaks* is used to describe school-breaks at the primary and secondary education level in the period of interest (Jan. to March). The specific naming and purpose varies. Multiple regions have winter sport-holidays, others carnival/crocus and some even early spring breaks. All of these different types of breaks are called school-breaks. Indicative of clustered travel during these breaks in Europe is the fact that the timing of these breaks is collected and used to predict crowding at tourist destinations (see e.g. the website `https://avoid-crowds.com/`).

[5] Evidence from Denmark and Iceland could be traced to the ski-resort Ischgl in Austria. See Gudbjartsson et al. (2020) and Bluhm et al. (2020). Notable as well that during extensive contact tracing in Iceland in March/April 2020 only 2 of the 200 cases could be traced to foreigners/tourists. Hence, the bulk of the initial spread could be attributed to locals returning from abroad and related subsequent spread (Visir, 2020).

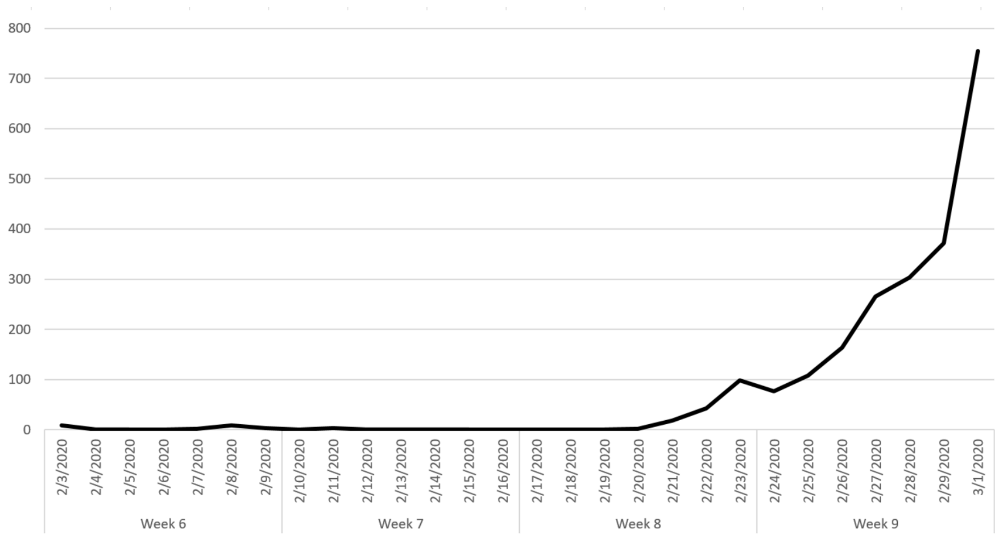


Figure 2: The number of new confirmed cases of Covid-19 in Europe in late February/early March 2020. *Source: Hasell et al. (2020)*

of confirmed cases were being reported in weeks 6 and 7 and only after February 20 did the number of (confirmed) cases start increasing rapidly. We can therefore broadly generalize the likely impact of the school-breaks by week.

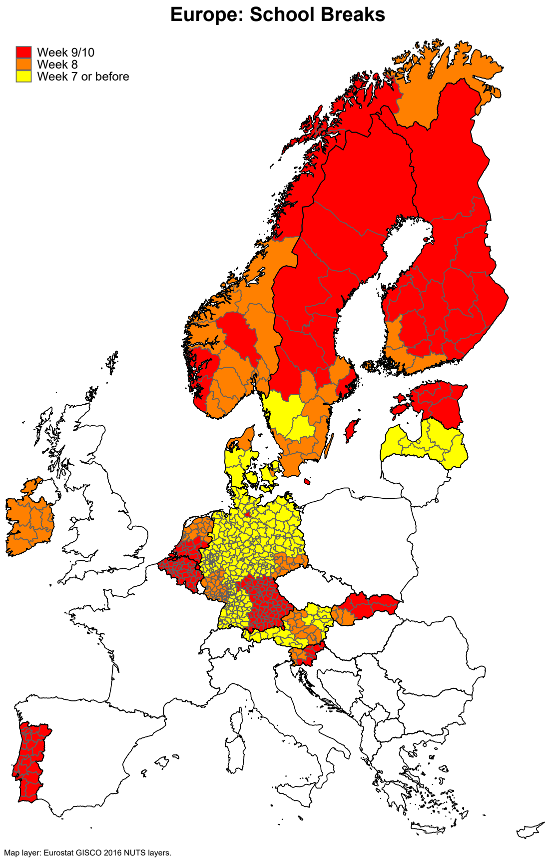
- **Week 7 (10-16 February or earlier):** A school-break during or before week 7 is not likely to spark a large pandemic as the spread of Covid-19 was sporadic/localized with the number of confirmed daily cases below 10 in Europe.
- **Week 8 (17-23 February):** By the end of week 8 the number of reported cases was increasing suggestive of local transmission. Number of daily cases reached around 100.[6]
- **Week 9 (24 February -1 March):** During this week the number cases increased rapidly with daily cases above 750 by the end of the week.
- **Week 10 (2-8 March):** During week 10 the exponential spread continued with over 2000 daily cases at the end of the week. From late week 10 and start of week 11 the severity of the pandemic becomes more tangible through, for example several, large (global) stock market declines (March 9th, 11th, 12th and 16th), WHO declared Covid-19 a pandemic and the US travel ban on many European countries (both on March 11th).

[6] On February 19th the Champions League football game between Atalanta and Valencia was played. This game, often dubbed as “Game Zero”, is thought to have been a super-spreading event sparking the initial spread in Northern Italy. The game was held two days before the first confirmed locally transmitted case in Italy. The number of confirmed cases in Bergamo, home of Atalanta, skyrocketed following the game and over a third of the Valencia team became infected (AP news, 2020). In Spain the game is thought to contributed to the initial spread along with other events during the same week as discussed by SeqCOVID (2020) and López et al. (2020). A gathering between 17-24th of February in Mulhouse is thought to have played a large role in the spread in France. Of the 2500 participants, at least halve are thought to have become infected (Point.fr, 2020). The closure of 120 schools in France was announced on March 3rd, located in three different regions spread over the country: Northwestern Morbihan, Oise north of Paris, and the department Haute-Savoie in eastern France (RFI, 2020).

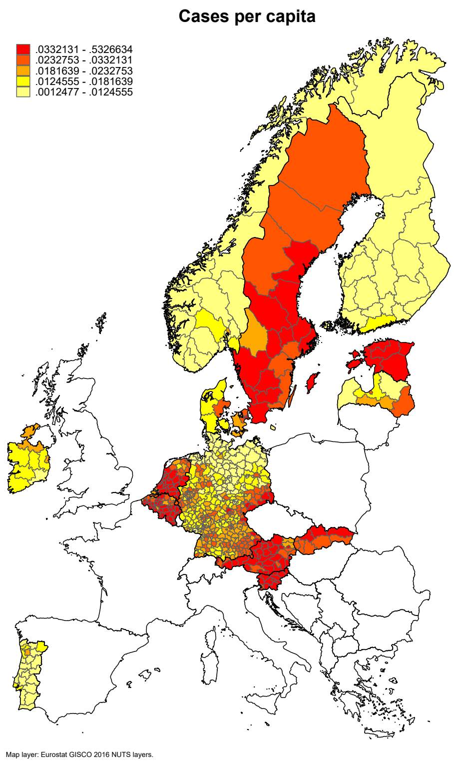
It is important to stress that the number of cases during these weeks is now known to have been grossly underestimated as most cases were undetected (see e.g. Li et al., 2020). However, the numbers give a good picture of how the spread of Covid-19 was *thought* to have been at the time. Public awareness of the seriousness prior/during travel was low until late week 10 (early week 11). Hence, a traveler in week 6, 7, 8 or 9 would only see a limited number of confirmed cases prior to travel (in weeks 5, 6, 7 and 8) but the likelihood of being exposed to Covid-19 would be vastly different. Unaware individuals traveling in the high-exposure week 9 are therefore likely to have been a human transport of Covid-19 to their local area. During the short time window around week 9, the risk of being exposed to Covid-19 during travel was high while the *perceived* risk was low. As the awareness of the risks was still rather low on return, these individuals are in addition likely to have started their normal lives before the seriousness of the spread was apparent across Europe, amplifying the local geographic exposure. A similar argument applies for week 8, but from a lower base. While the spread was higher in week 10, than 9, the seriousness was more noticeable and hence less clear if week 10 travelers are more or less likely to have brought Covid-19 to their home region.

School-breaks in Europe vary considerably both within and across countries. Some countries lump the break in a single week (Belgium in week 9) others stagger the break over multiple weeks (e.g. Netherlands, Sweden, Germany, Slovakia, Denmark). Given the timeline constructed above we expect the likelihood of a regional outbreak to vary substantially depending on the week of the school-break. Regions with a school-break *prior or during* week 7 are not likely to experience outbreaks, but as the pandemic intensifies over time the likelihood increases of a large clustered outbreak on return from travel. The school-breaks may therefore lead to both within and cross-country variation in the initial spread of Covid-19. In this paper we limit the scope to countries were: 1) the regional variation in school-breaks is clear and clustered in both time and space, and 2) the domestic spread did not take off due to other events during the breaks.[7]

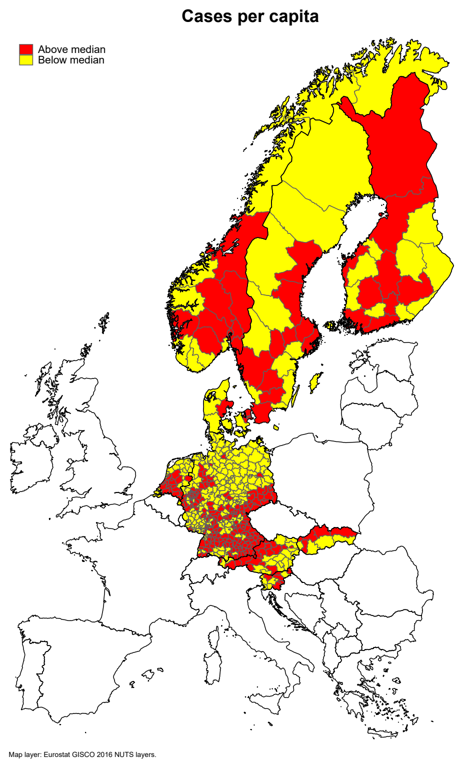
[7]Large outbreaks in week 8, such as discussed above in footnote 6, would tend to attenuate the impact of the school-breaks as they will create different spatial patterns. In France, such early super-spreading events combined with that the schools-breaks are two week long, and partly overlap, will tend to reduce the clustering (in time/space) and likely importance of school-breaks for the spread. The domestic spread in Italy/Spain increased earlier as is even visible from figure 2. The variation in school-breaks is also unclear, while some regions/cities in both countries have some school-break in part of week 9. Italy, Spain and France are therefore excluded from this analysis. A number of (eastern) European countries are also excluded that have unclear (or no) variation in breaks (e.g. Romania, Croatia, Greece, Czech-Republic, Hungary, Luxembourg, Iceland) or lack of Covid-19 data at fine geographic level (Poland). UK is also excluded due to lack of school-break variation and introduction of a new (potentially more contagious) strain in the fall. See appendix 5.1 for more information.



(a) School-Breaks in Europe



(b) Cumulative number of cases per capita by NUTS 3 region.



(c) Cumulative number of cases per capita by NUTS 3 region relative to *country* median.

Figure 3: Comparison of school-breaks and cumulative number of Covid-19 cases (as of early December 2020).

Note: Selected countries, see discussion in footnote 7. Figure 3c restricted to countries with variation in school-breaks. See appendix 5.3 for descriptive statistics on the school-breaks by country. See the data appendix 5.2 for information on the classification of the school-break in one German State (Mecklenburg-Vorpommern). *Source:* Naqvi (2021a) is used to construct the cases numbers in (b, c) and for the source files for mapping.

From figures in 3 we can see a comparison of the cumulative number of cases per capita up to early December 2020 and a comparison with school-break weeks.[8] The map shows the number of cumulative cases of Covid-19 per capita (b) and the number of cases in a country relative to the median in that country (c). Investigating these maps we can see some clear patterns. In the Netherlands the southern part (week 9 break) has been harder hit than the northern week 8 break regions. Looking within Germany, regions with breaks in weeks 8-10 have relatively higher number of cases of Covid-19. Belgium, the hardest hit country in the EU, has a nationwide school-break in week 9 as well as Stockholm, the badly affected capital of Sweden.

3 Data and Estimation

To investigate if school-breaks in weeks 8, 9 and 10 led to large outbreaks in the spring and can explain subsequent spread of Covid-19 we first collect data on school-breaks across Europe. The main source on school-breaks is Eurydice (2019), established by the European Commission, which collects information on the structure of the school year in Europe before each school year. This is then cross-referenced with other sources.[9] Several datasets on the spread of Covid-19 are used. First, data collected and harmonized by Naqvi (2021a) on case counts of Covid-19 at the NUTS 3[10] level for a number of European countries. For the first part of the analysis, I use Covid-19 case numbers from 649 regions in 14 European countries.[11] Secondly data from RKI Germany and RIVM in the Netherlands are used for other outcomes (hospitalizations, deaths) or data at a more detailed geographic level. See the data appendix for more information.

To assess if the timing of school-breaks is important for the spread of Covid-19 we run a standard OLS regression to estimate equation 1. In this regression we try to explain the number of cases of Covid-19 per NUTS 3 region (ln number of cases) with a single joint dummy variable for regions that have school-breaks in weeks 8, 9 or 10. As the dates of the school-break are decided long in advance the timing is naturally exogenous to the spread of Covid-19 in February/March 2020. A significant coefficient for β_1 enables us therefore to *causally* infer the

[8] Some descriptive statistics on the break weeks can be found in appendix 5.3.

[9] The websites www.Feiertagskalender.ch and Expatica.

[10] The NUTS classification is a hierarchical system used in the EU based on administrative borders. NUTS 3 are small regions, NUTS 2 are larger areas while NUTS 1 are major socio-economic regions.

[11] We restrict the countries to those we expect school-breaks to have led to large outbreaks in the spring. See earlier discussion.

role of school-breaks on the spread of Covid-19.

$$ln(cases)_r = \beta_1 break_r + region_r + CD_c + \epsilon_r \quad (1)$$

I run the regression separately for each month (10 regressions) [12] to investigate not only if late school-breaks (in weeks 8-10) were important for the initial exposure but also persistence over time. A number of NUTS 3 specific control variables ($region_r$) from Eurostat are added.[13] The inclusion of these variables controls for the cross-region demographics and importantly variation in population density in terms of number of inhabitants, typology (urban-rural) and geographic size. Errors are clustered at the NUTS 2 level.

Recall that in equation 1 we include dummy variables for regions that have a school-break in either week 8, 9 or 10. In practice this means that we are comparing regions that had breaks in these higher exposure weeks to regions that had breaks in week 7 or earlier (controlling for demographic variables as noted above). In addition we add a country specific dummy (CD_c) to the regression. As we know testing strategies vary significantly *between* countries and the inclusion of such a country specific effect accounts for such differences. By using a country specific dummy we are effectively using variation *within* a country to identify the effects.[14] As the response in the spring was mostly *country* specific, containment policy should not play a large role in the relative distribution of cases *within* a country. The country specific fixed effect will, for example, capture country specific lockdowns or other containment policies.

Figure 4 shows the OLS estimation results from these *ten* monthly regressions. We can see clearly that regions with a school-break in week 8, 9 or 10 had a considerably higher spread of Covid-19 in March-April. Quantitatively the difference between late and early break regions is large. We see that the number of cases in March is around 60% higher for regions with a school-break in either week 8, 9 or 10 (compared to those with a break in 7 or before).

A natural extension is to investigate if specific week numbers matter more than others as we

[12] The cases are first aggregated to 7-day intervals and then to the monthly level which roughly correspond to a month.

[13] These include a categorical variable on urbanization (three categories predominantly urban, intermediate and predominantly rural), population, regional income, area(km sq.), median age and percentage of people below 14 and share above the age of 60.

[14] Note that countries with the same school-break profile may still experience a variation in the overall level of cases coming in to the country stemming from the country specific propensity to travel abroad during the break. See also a discussion in appendix 5.2 on travel patterns to the known hot-spots in the Austrian alps in February and March 2020.

may expect from the timeline presented above. We can alter equation 1 and instead of a single post-week 7 dummy include separate week specific dummies as shown in equation 2:

$$ln(cases)_r = \beta_1 break8_r + \beta_2 break9_r + \beta_3 break10_r + region_r + CD_c + \epsilon_r \tag{2}$$

We estimate equation with OLS as before using the same control variables. The coefficients for the week specific dummies are shown in sub-figures 4b, 4c and 4d. We can see that the initial impact is strongest in regions with a school-break in week 9 (over 90%) secondly in week 10 (50-95%) and lowest in week 8 (35%). As before these results are relative to regions that had a break in week 7 or before.[15]

One potential amplifying factor for regions with breaks in weeks 9 and 10 is that since Covid-19 had been introduced to a country by week 8 (9) travelers, international travel may not be needed transport the virus to a new region within the country. Hence, *domestic travel* to newly infected regions with breaks in earlier week(s) may have amplified the impact for regions with breaks in weeks 9 and 10.[16]

3.1 Persistent Breaks!

Above we have established that school-breaks in weeks 8, 9 and 10 are a strong indicator of large-breakouts of Covid-19 in the spring of 2020. The second and main objective of this paper is to show how initial exposure is still relevant during the fall/winter of 2020. We can see from the sub-figure 4a that despite the apparent disappearance of the initial breakouts the impact re-appears after the summer holidays. This can be seen from the re-emergence of a significant break-week dummy from September and on-wards. On average the spread is 30-50% higher in areas with high likelihood of exposure (week 8, 9 or 10). Investigating the persistence separately by school-break week we can see an indication that the persistence is proportional to initial

[15] In some cases the school-breaks vary *within* a NUTS 3 regions (e.g. Netherlands, Denmark and Sweden). Such variation will tend to attenuate the results presented above and bias the coefficients to zero, our results may therefore provide an underestimate/lower bound of the true effect in such cases.

[16] The spread will also be less clustered over time in Europe (e.g. away from ski-resorts) and travel to other destinations may become risky at this point. An example of such cases are discussed in Lemieux et al. (2020), e.g. an international business conference in Boston during week 9 (February 26-27). Bluhm et al. (2020) also show by analysing genome sequences that some cases of Covid-19 were likely transmitted from Denmark to Sweden in March 2020. This is consistent with school-breaks potentially being important since the breaks in Denmark are mostly in weeks 7/8 while the receiving areas are mostly in northern Sweden (week 10). The results are also robust to adding gravity variables related to Ischgl as in Felbermayr, Chowdhry, and Hinz (2020) and other related robustness checks. See appendix 5.2 for a discussion.

exposure with the earliest and strongest resurgence in areas with breaks in week 9 (40-70% higher). This suggests that the size of the breakout impacts the degree of latent spread in an area, driving the systematic re-resurgence of Covid-19 in the fall of 2020. Large outbreaks will therefore have long-lasting consequences on community spread since it may be difficult to capture or suppress the underlying (latent) spread fully.

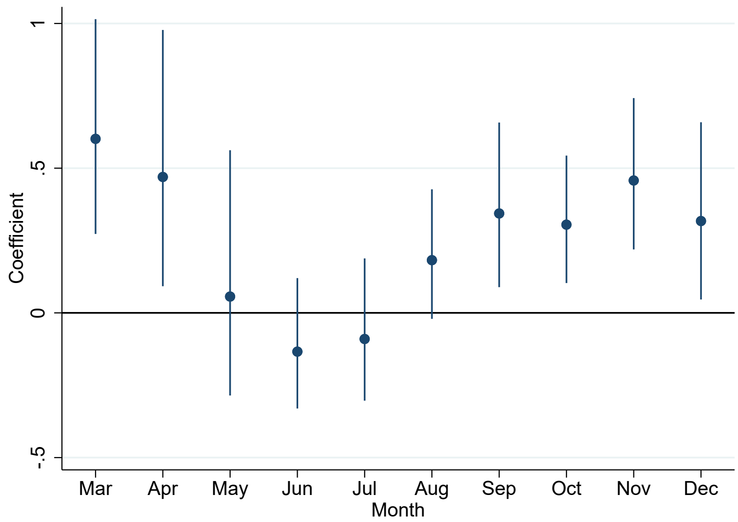
One may be worried about regional containment measures impacting these results. However, it is important to note that such policies are generally skewed to the areas with high levels of spread. As shown before these are the areas that had breaks in weeks 8, 9 and 10. Regional containment policies would therefore tend to bias the results to zero and the persistence would therefore be *stronger* if not for such policies.[17]

While the geographic footprint that the school-breaks 2020 left behind are still visible in the fall/early winter, we would expect the systematic differences to subside as more local outbreaks occur over time. In a standard epidemiological SIR model for example, infectious individuals pass on the virus to the susceptible population. Over time, as more and more people get infected, the population of susceptible individuals reduces, eventually slowing down the spread until herd-immunity is reached. In our setting, this would eventually lead to convergence between the initially hard hit areas and those less exposed, as herd immunity should be reached earlier in the highly exposed regions. However, as long as the share of people that are immune is fairly low, convergence between high- and low exposed areas would only occur gradually.[18] To reach herd-immunity a sizable share of the population needs to be immune to Covid-19, either by vaccination or antibodies. A recent study estimated that over 60% (and up to 90%) of the population would be needed to reach herd-immunity (Anderson et al., 2020). A Spanish nationwide study of over 51 000 individuals, conducted in November 2020, showed however that

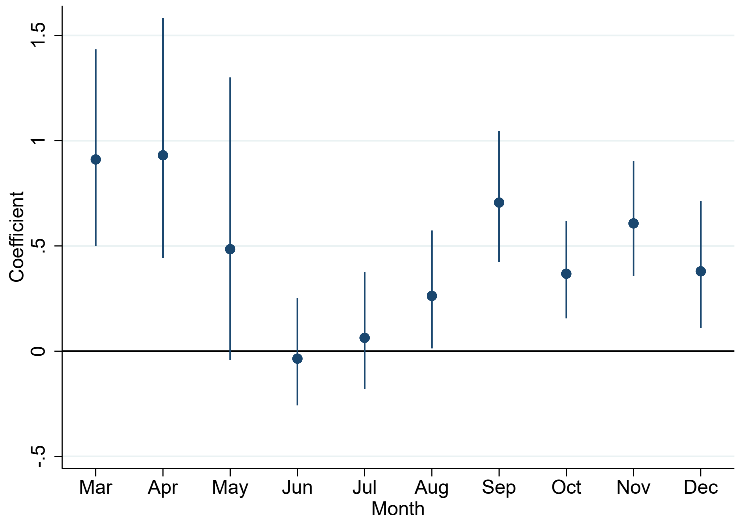
[17] A number of hard hit countries/regions started to re-introduce stricter containment policies in September and October. While local authorities in Germany have autonomy in imposing restrictions the German federal government put in place a trigger-based system were local authorities were advised to consider imposing lockdowns if new cases went above 50 per 100 thousand residents (Han et al., 2020). Germany introduced a nationwide "lockdown ligth" from beginning of November and a full nationwide lockdown from mid-December. Note that two large regions, Bavaria (week 9), and Saxony (week 8) went into a stricter lockdown prior to the full lockdown which came into effect on December 16th. In the Netherlands stricter measures were announced on September 18th for six security regions (of 25). All of which had (mainly) breaks in week 9. On September 25th eighth more regions received the tighter measures, six of which had breaks in week 9, two in week 8. Soon thereafter more national measures were introduced, a partial lockdown from mid-October and a full lockdown from mid-December. This provides indications that the persistence may be underestimated due to targeted regional policy in hard hit regions. A successful nationwide lockdown would also likely tend to reduce the overall level of the spread and hence observed regional difference, in a similar way as the convergence over the summer.

[18] Outbreaks in initially low exposure regions would also tend to lead to convergence over time and reduced importance of the school-breaks.

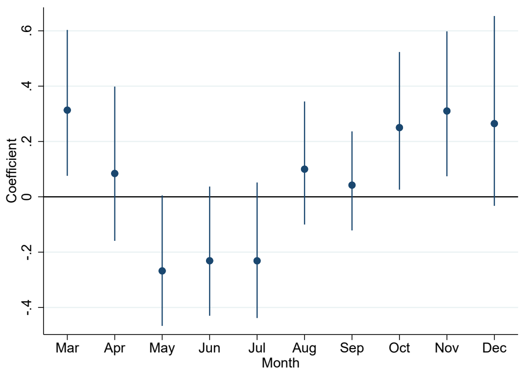
the share of people with antibodies was only 10% nationally and under 19% in the hardest hit areas (The Ministry of Health and ISCIII, 2020). As Spain has experienced relatively large outbreaks of Covid-19 (see figure 1), it strongly suggests that the share of immune individuals is still well below the levels needed to reach herd immunity in both Spain and the rest of Europe during the period of interest.



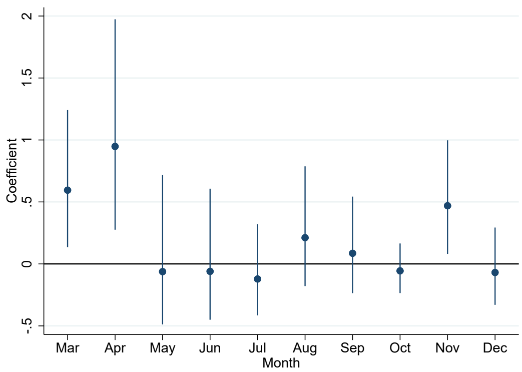
(a) Cases: Joint dummy (8, 9 or 10)



(b) Cases: Week 9 dummy



(c) Cases: Week 8 dummy



(d) Cases: Week 10 dummy

Figure 4: Coefficient plot of the joint dummy per month in graph 4a. Sub-graphs 4c,4b 4d show week 8, 9 and 10 dummies (in a single regression without the joint dummy).

Note: The coefficient on the break dummies are semi-elasticises in equation 1. The coefficients in the diagrams have been transformed ($e(\beta_1 - 1)$) for easier interpretation. A coefficients of 0.5 in the diagram can be interpreted as the spread being 50% higher relative to regions with breaks in of before week 7. The full results are available in the appendix, tables 5 and 6.

3.2 Deaths and Hospitalizations

It is well established that the number of Covid-19 tests varies between countries.[19] For our identification strategy such cross-country variation in testing is captured by a country specific fixed effect (CD_c). Regional variation within a country may however impact the results if the number of tests is *disproportionately* higher in regions with school-breaks in weeks 8, 9 and 10. This could for example be due to better public access to testing in these regions.[20] To investigate if (within-country) regional variation in testing impacts our results we can use other outcomes which do not rely on public access such as the number of Covid-19 related deaths and hospitalizations. If such public access bias impacts our results then we would not expect the same bias to be present in hospital settings.

To investigate this we use data from Germany and the Netherlands.[21] The German RKI publishes data on the number of cases and Covid-19 related deaths for each NUTS 3 region. Germany is particularly well suited for this purpose due to geographic and population size, large number of NUTS 3 areas, wide-spread testing from early stages and variation in timing of school-breaks.[22] It is therefore natural to investigate it further. We can see from the figures in 5 that the broad patterns are the same. Using the joint dummy model or separate week dummies (week 8 or week 9/10 combined) the results show the same trends.

An alternative outside of Germany, is data from the Netherlands who report the number of deaths and hospitalizations at the municipality level. This dataset has the additional benefit that we can investigate the impact at a more detailed level.[23] Figure 6 shows similar results, with particularly clear patterns in regards to hospitalizations in sub-figure 6a.[24] It is important

[19]See for example data from Hasell et al. (2020).

[20]Using the school-break weeks to identify regions with high likelihood of initial exposure is a strength of the study as we can overcome potential problems related to limited initial testing capacity in some countries (importantly not Germany) or in relatively more rural areas. Note also that if testing capacity was limited and, for example, regional capacity was reached during March/April this may tend to bias the results downward as the limit would be reached first in the high-exposure areas. Note however that in some countries the testing is controlled at the regional level (e.g. Sweden) which is less applicable. This discussion underscores the importance of exploring the robustness of the results using other Covid-19 related outcomes.

[21]Both countries had a large number of people traveling to the known hots-pots in the Austrian alps in February. The Netherlands has for example the highest share of nights spent (per capita) and the regional patterns of travel to Austria from German regions are consistent with clustered travel during the school-breaks. See a discussion of the travel patterns in appendix 5.2.

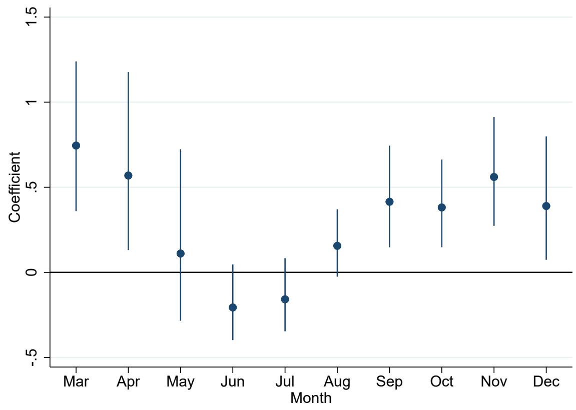
[22]Germany has homogeneous regional rules for testing as discussed in Mitze et al. (2020). For information on early testing capacity see Financial Times (2020).

[23]As mentioned before school-breaks vary at a more detailed level than NUTS 3 in some countries. In such cases we can overcome the potential attenuation bias by using municipality level results.

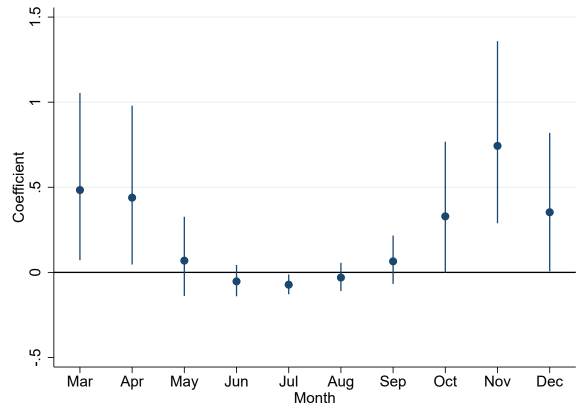
[24]Similar overall patterns found for deaths but not significant from the fall.

to highlight one difference for the Netherlands compared to Germany and the broader results. The comparison group in this case are municipalities with a break in *week 8*. Hence, given that we expect week 8 municipalities to be considerably impacted as well the results for week 9 should be less sharp compared to the previous results when *both* week 8 and 9 were compared to regions with a break in *week 7 or before*.[25]

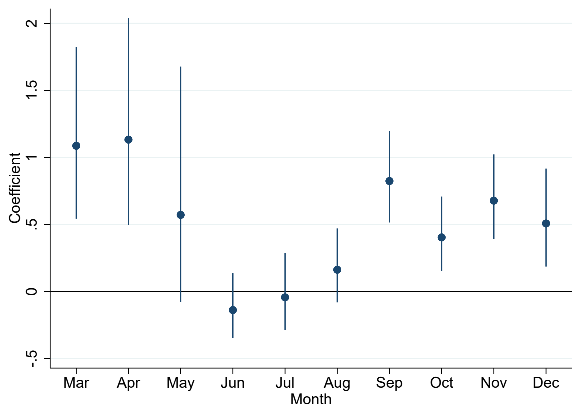
[25]The level of testing in the Netherlands was low during March and April and less than half (per capita) of that in Germany (Hasell et al., 2020). In late March some regions, that had received relatively fewer cases, started to test more generally and depart from the national testing strategy to test only those with symptoms (DutchNews.nl, 2020). Since *all* of these regions had breaks in week 8 this would tend to bias the initial week 9 results down in Netherlands (as relatively more cases are captured in week 8 areas). From June 1st, the testing became more general nationally and the number of tests increased sharply (Hasell et al., 2020). This can be seen in the results of figure 6c as more cases are captured in week 9 municipalities. Note that since the data is first transformed to 7-day intervals and then to months the first couple of days after the rules changes are classified with the month of May. Note that hospitalizations/deaths do not suffer from this limitation in the Netherlands were the patterns are similar to before.



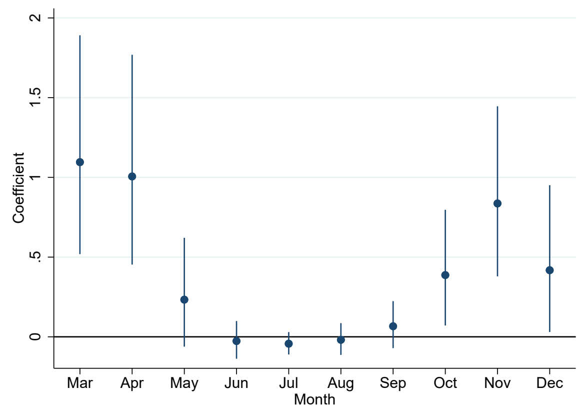
(a) Cases: Joint week 8/9/10 dummy



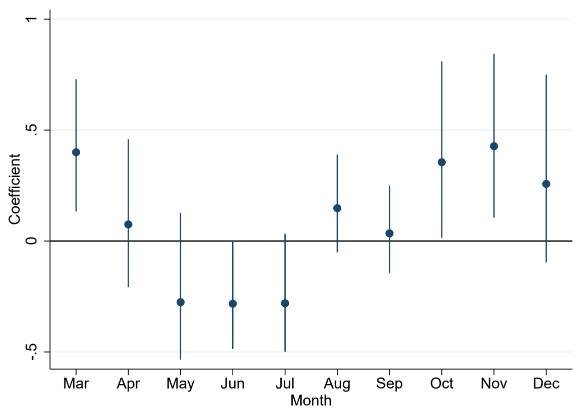
(b) Deaths: Joint week 8/9/10 dummy



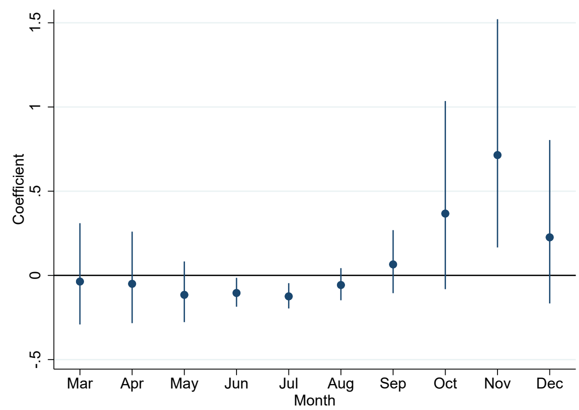
(c) Cases: Week 9(10) dummy



(d) Deaths: Week 9(10) dummy

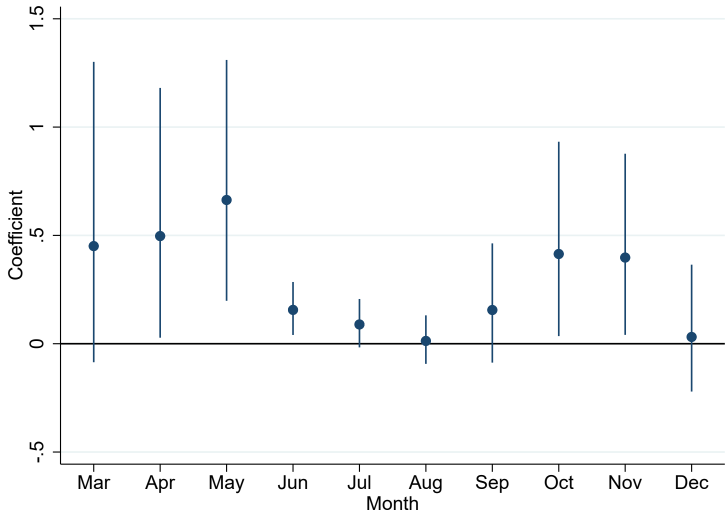


(e) Cases: Week 8 dummy

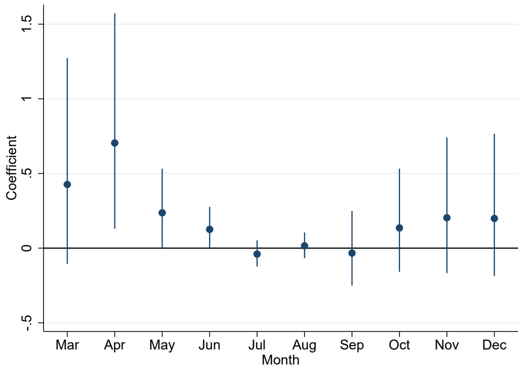


(f) Deaths: Week 8 dummy

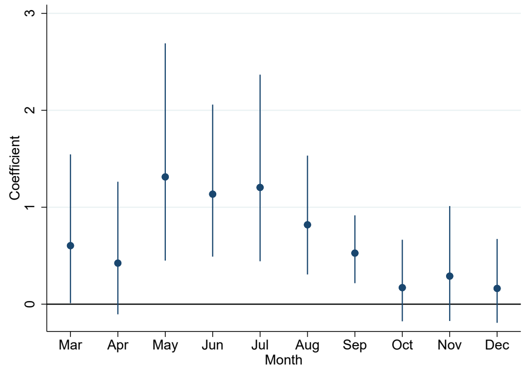
Figure 5: Germany only: Results for the number of cases and deaths (joint week 8/9/10 dummy or separately week 8 and week 9(10) dummy. Robust standard errors clustered at NUTS 2 level.



(a) Hospitalizations



(b) Deaths



(c) Cases

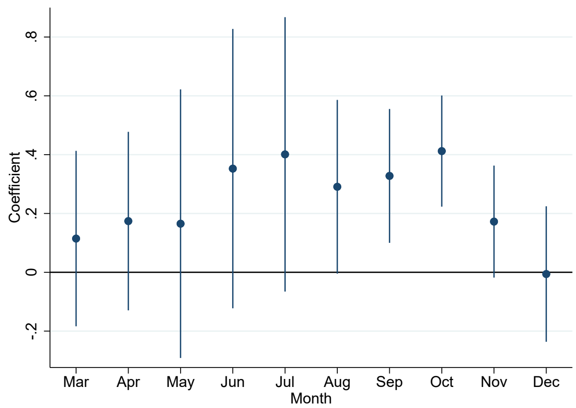
Figure 6: Netherlands: Coefficient plot of the week 9 dummy per month. Outcome variable is either hospitalizations (6a), deaths(6b) or cases(6c).

Note: From the previous section we know that regions with school-breaks in week 8 tend to be have a sizeable school-break effect compared to those with even earlier breaks. The results are therefore not directly comparable to those in figures 4 where the comparison group consists of regions with school-breaks in 7 or earlier. The coefficients in the diagrams have been transformed ($e(\beta_1 - 1)$ as before for easier interpretation. Robust standard errors clustered at NUTS 3 level. See appendix 5.1 and tables 12, 13 and 14.

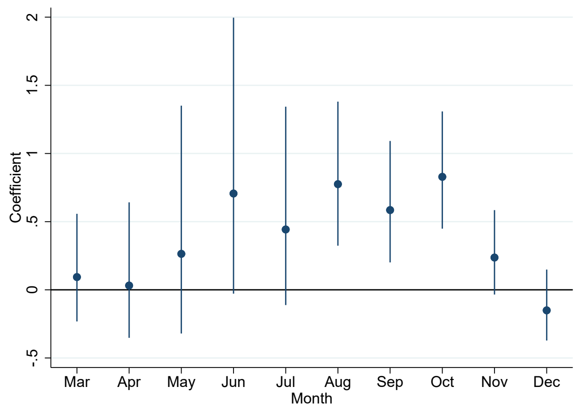
3.3 Urban or Rural Persistence

Urbanization is often discussed in relation to the spread of Covid-19 and many cities have experienced large breakouts (e.g. New York, Madrid, Stockholm). A concern may therefore be that the result are driven by urban areas with high initial exposure. As we expect the degree of latent spread to be relatively higher in both urban and rural areas which had high likelihood of initial exposure (week 8, 9 and 10), the persistence should even be seen even in more rural areas.

To investigate if and what role urbanization plays for the persistence of Covid-19 we add an interaction term for the joint break dummy (week 8, 9 or 10) and our categorical variable for urbanization. The results show that the degree of persistence is *stronger* in *more* rural areas. It should be noted that the *level* of the spread of Covid-19 is higher in urban areas but from the graphs we can see that the *persistence* related to initial exposure is higher (as can be seen from a significant interaction in the fall). The persistence is roughly 30% higher in intermediate urban areas and over 50% higher in rural areas in the fall. This suggests that Covid-19 persists even in smaller more remote settings that experienced high initial exposure and not only in urban settings. A potential explanation could be that containment policies have been more targeted at urban areas, and underestimated the potential persistence of Covid-19 in relatively rural communities.



(a) Intermediate urbanization



(b) Rural

Figure 7: Urban/rural differences

Note: This table shows the interaction of urbanization dummy and the joint week 8, 9 and 10 dummy. The interaction compares if the persistence is different in either predominantly rural or intermediate areas compared to predominantly urban areas (cities). A significant effect shows that the initial exposure is more important for more rural areas compared to cities (predominately urban). Results are transformed as before. See also table 7 for full results.

4 Conclusion

While the spread of Covid-19 was sporadic and localized in Europe at the beginning of February 2020 the corona virus was spreading at an alarming rate by the end of the month. This paper explores the role of school-breaks during this *key period* in sparking large initial outbreaks and persistence over time. The combination of the clustered nature (time/space) and *exact* timing of the school-breaks during this period led to a vastly different likelihood of returning travelers transporting the virus back to their local community.

The two main contributions of the paper are the following. First, I find that having a school-break from late-February (weeks 8, 9 and 10) led to 60% to over 90% higher *initial* spread of Covid-19 (compared to other regions in the same country). The results suggest that the school-breaks 2020 (in weeks 8, 9 and 10) were a region-wide super-spreading event. Secondly, even after the apparent containment of Covid-19 over the summer the same patterns re-emergence and the spread is consistently 30-40% and up to 70% higher in the regions with school-breaks in weeks 8, 9 and 10. In particular, I find that regions with school-breaks in week 9 experienced both the largest outbreaks in the spring the strongest resurgence from the fall (e.g southern-Germany, southern-Netherlands, entire Belgium, Stockholm). The results therefore suggest that the underlying latent spread is relatively higher in areas that have previously experienced large outbreaks, even when such systematic differences are not visible (e.g. over the summer).

The main policy consequences of the results are that once a *large* outbreak of Covid-19 has occurred it persists in the region. Rapid measures to avoid the *first* large outbreak are therefore fundamental to long-term containment. While avoiding large outbreaks of Covid-19 will entail short-term containment costs, the benefits may be long-lasting. The strong degree of regional persistence combined with the observed seasonality of Covid-19, also stresses the need for effective vaccinations during the first half of 2021, to avoid a new wave of cases in the fall. This especially applies to regions that have experienced large-outbreaks but are well-below the levels needed for herd-immunity as they may be particularly vulnerable. More broadly, the results are also indicative of the benefits of avoiding initial exposure to other strains/mutations of coronavirus, which may be more contagious.

Lastly, the school-breaks provide an exogenous measure of initial exposure to Covid-19 (or underlying spread) for a number of European countries that can be important to account for when evaluating the effectiveness of containment measures or other policies.

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5 Appendix

5.1 Data Appendix

Naqvi (2021a) has collected and harmonized daily Covid-19 case data for a number of European countries at the NUTS 3 level. The 14 countries used for this analysis are the following: Austria (AT), Belgium (BE), Denmark (DK), Germany (DE), Estonia (EE), Finland (FI), Ireland (IE), Latvia (LV), Netherlands (NL), Norway (NO), Portugal (PT), Sweden (SE), Slovenia (SI) and Slovakia (SK). See table 2. The version 1.2. from early January 2021 is used for this analysis. Documentation of the harmonization, change-log, code and original sources for each country can be found on the Github page of the project (Naqvi, 2021b).

The German data comes from *The Robert Koch Institute* and includes the number of cases and deaths on a daily basis at the NUTS 3. Data on Germany is sourced from Gehrcke (2021). The data for the Netherlands comes from RIVM (2021). For the regressions using data from the Netherlands only, the Eurostat controls on demographics are at the NUTS 3 level. Population, area and urbanization data are at the municipality level either from Eurostat or ArcGis open data(ArcGis, 2021). For information on school-breaks at the municipality level in the Netherlands comes from the official governmental website (Government.nl, 2021).

5.2 Travel patterns, school-breaks and distance

The state of Mecklenburg-Vorpommern in Germany has a school-breaks that is somewhat unclear how to classify. The official dates for Mecklenburg-Vorpommern range from 10-21 February (defined as week 7) while, for comparison, the Saxony (official dates from 10-22 February) and Saarland (official dates 17-25 Feb) are both defined as week 8. There are several reasons why Mecklenburg-Vorpommern is classified as week 7. First, districts in Mecklenburg-Vorpommern are rather remote and furthest away from known initial hot-spots in the Alps. For our our purposes, since the break both ends first and the state is most remote of the week 8 areas in Germany this would likely lead to travelers *starting* their return earlier than those in other week 8 states in Germany (roughly 400km south). As discussed above in section 2 the spread was taking of during these pivotal days and finishing a break earlier *within* week 8 may therefore lead to variation in likelihood of exposure. Secondly, the break in 2020 is Mecklenburg-Vorpommern started a week later than the three preceding years (begun on 4-6th of February). Saxony has for comparison begun breaks starting from 12-18th of February in previous years. If the timing of travel is somewhat sticky between years it may lead to travel being relatively skewed to early part of the break in Mecklenburg-Vorpommern while to the late half in Saxony/Saarland. To see if this classification impacts the results we change the definition of Mecklenburg-Vorpommern to week 8 and the results are similar (impacts only week 8). The results are shown in appendix 5.5, figure 8.

Austria is an example of a known hot-spot in late February and early March (CNN, 2020). It is therefore natural to investigate the travel patterns to Austria during this period. From official Austrian tourism data (Statistics Austria, 2020) we can see that just below 2,7 million tourists visited the Austrian alps in February (three largest areas only: Tyrol, Salzburg, Voralberg). Investigating the origin country/region breakdown and duration of stay we can see that the largest groups of visitors come from Germany, Netherlands, Belgium, Denmark and Sweden. Together they account for over 2 million visitors. From table 1 we can see considerable regional variation in the intensity of travel to Austria across German regions. Eastern-Germany and Berlin have the highest intensity of travel as measured by average time spent in the Austrian Alps (120 and 116 number of nights per thousand inhabitants). A combination of a large number of guests, relative to population, and long average duration is consistent with the fact that all the eastern regions and Berlin had extended breaks sometime during February. With the high intensity of travel but relatively early school-break during (3-8 February, week 6), Berlin likely escaped a (very) large initial outbreak.

Table 1: Number of visitors in Austria in February 2020 (March col. 7-8 only) and average duration by country/region of origin and relation to school-breaks.

				Per inhabitant		March		
	Nr. visitors	Nr. nights	Dura.	Visitors	Nights	Dura.	Nights	**Note on February school-break**
Germany	1,339,005	6,237,466	4.7	16.1	75	5.8	28	-
Bavaria	*358,177*	*1,316,837*	*3.7*	*27.4*	*101*	3.7	33	Week 9
Baden Württemberg	*229,990*	*963,309*	*4.2*	*20.8*	*87*	4.2	26	None
North Rhine-Westphalia	*143,973*	*699,028*	*4.9*	*8.0*	*39*	7.8	24	None
Central Germany	*182,189*	*871,170*	*4.8*	*16.1*	*77*	5.8	31	Rheinland-Pfalz and Saarland (week 8)
Northern Germany	*104,397*	*494,772*	*4.7*	*7.8*	*37*	9.5	36	No extended breaks (two days at most)*
Eastern Germany	*243,683*	*1,454,867*	*6.0*	*19.4*	*116*	6.8	19	Breaks in all states during weeks 6-8
Berlin	*76,596*	*437,483*	*5.7*	*21.0*	*120*	6.9	22	Week 6
Belgium	104,636	596,238	5.7	9.0	51	5.9	9	Only week 9.
Denmark	86,885	480,160	5.5	15.0	83	8.6	13	Mostly week 7. Suburbs of CPH in week 8
Finland	9,743	47,737	4.9	1.8	9	6.9	3	Weeks 8-10. Helsinki week 8.
Netherlands	470,605	2,682,674	5.7	27.5	157	6.7	33	Week 8 or 9.
Norway	12,652	59,338	4.7	2.3	11	7	3	Weeks 8-10. Oslo week 8.
Sweden	42,323	240,827	5.7	4.2	24	8.4	5	Week 7-10. Stockholm week 9.

Note: The data from Statistics Austria groups German states in the following way: Central Germany: Hesse, Rhineland-Palatinate, Saarland. Northern Germany: Lower Saxony, Hamburg, Bremen, Schleswig-Holstein. Eastern Germany: Saxony, Saxony-Anhalt, Thuringia, Brandenburg, Mecklenburg-Vorpommern. The numbers in columns 5-6 and 8 are per inhabitant of the origin region/country (in thousands). Columns 7 and 8 (for March) can be compared to columns 4 and 6 (for February). *Hamburg in Northern Germany, is the only German NUTS 3 region that has a break in the beginning of *March*. See discussion in appendix 5.2.

We can also compare these regions to the similarly distant North Rhine-Westphalia and northern-Germany *do not* have a break in February. From table 1 we can see that the eastern regions and Berlin have a three-times higher level of travel (nights per capita), consistent with clustered school-break travel. North Rhine-Westphalia and northern-Germany also share a border with the Netherlands and Denmark which have much higher level of travel. From table 1 we can see that people from the Netherlands spend on average the most nights in the Austrian alps during February (157 nights per thousand inhabitants). A notable difference is that the Netherlands has a school-break in week 8 or 9. We can even see high level of travel from Denmark during the winter-break season in February consistent, with Bluhm et al. (2020) who trace the bulk of the genome sequences in Denmark to travel from Austria. Even in the south, relatively close to Austria, a difference can be seen in the travel between Bavaria (week 9) and Baden-Württemberg (none). While the numbers suggest some shorter day-travel to Austria, a clear difference in the number of guests and level of stay can still be seen from table 1 suggestive of clustered school-break travel.[26]

Another way to analyse if travel is clustered during the school-breaks is to zoom in on Hamburg in Northern-Germany. Regions in Northern-Germany do generally not have school-breaks in February and only Hamburg has a 2-week long break in early March. Hence, if school-breaks influence travel patterns we would expect this to be seen in the data for March. From table 1 (columns 7-8) we can see that in March 2020 the inhabitants of Northern-Germany had the longest duration of stay and spent the most nights per capita in March. The level is similar to February (36 v.s. 37) despite the general large drop in the number of tourist nights in Austria in March. This is a sharp difference from February when Northern-Germany had the lowest level (see columns 6 and 8 in table 1). As Hamburg accounts for less than 15% of total population of the Northern-region this indicates that the travel from Hamburg was substantial.[27] Another pattern from table 1 is the very sharp decrease in the level of travel from Berlin and eastern-Germany in March. These two areas had the highest number of nights per inhabitant in

[26] See also gravity robustness results below and results after dropping these two regions (see figure 11).

[27] Hamburg has a school-break in week 10 and 11 (defined as 10 in our analysis). As expected the overall level of travel falls sharply in March compared to previous years but we would expect the impact to be less pronounced in the very beginning of the month. We can investigate this hypothesis for Northern-Germany as we expect people on school-break in Hamburg to travel in that period. Investigating the data from Statistics Austria (2020) we can see that for March 2020, compared to March 2019, the number of nights spent in the Austrian alps decreased by only 24% for people coming from Northern-Germany. A reduction of 59% is seen for other regions of Germany. This is highly indicative of travel in the very beginning of March during the school-break in Hamburg. As the travel from the region is expected to be clustered in the very beginning of the month, it should be less influenced by the events starting in week 11 (see section 2). This is not driven by variation in school-break timing in Hamburg as it also had a two week long school-break in 2019 starting in early March. According to news reports 80 cases in Hamburg had been traced to Ischgl in late March and the resort was not fully quarantined until 13th of March (CNN, 2020).

February but the lowest in March consistent with clustered travel during the school-break weeks. Similarly the level of travel is still relatively low for North Rhine-Westpalia which does not have a break in either February or March.[28] This strongly suggests that the school-breaks have a substantial impact on when and for how long people travel to the Austrian alps, regardless of distance.

Felbermayr, Chowdhry, and Hinz (2020) estimate a gravity type model and find that distance alone to Ischgl in Austria explains a substantial fraction of the initial spread of Covid-19 in Germany (not using variation in school-break timing). In our main specification a country fixed effect is included which will capture the absolute and country-specific part of the distance to Isghl. Adding distance to the regression would therefore only capture relative distance to Ischgl *within* a country. Above we have established that the travel patterns to Austria align well with travel during a school-break and hence unclear what the relative distance would be capturing in the countries used in our analysis. However, to investigate if distance in general is important for the result I perform a number of robustness checks.

First, one way to investigate the role of absolute and relative distance is to remove the country specific fixed effect. While not preferred for our main specification, it allows us to investigate the role of absolute distance on the results. Hence, we rerun the regression without the country specify fixed effect but both with, and without, distance to Ischgl.[29] The results show that distance does not impact the results once the country-fixed effect is removed consistent with the timing of the school-breaks driving the results rather than proximity. See figure 9.

Second, as noted above, by including distance to Ischgl we can also investigate the role of relative within country distance to Ischgl.[30] After adding distance to Ischgl and including the country specific fixed effect the results are broadly similar. Note that initial impact in March/April is still large and highly significant for week 9 (around 50%) but appears somewhat

[28]Similarly for other countries we can see the largest *relative* decline between February and March in the average number of nights per inhabitant in Denmark (mostly week 7 and partly 8) and smallest for Finland and Norway (weeks 8-10) consistent with the structure of the school-breaks.

[29]Distance between NUTS 3 areas is drawn from the European Commission's Tercet distance matrix which has calculated the road distance between any two NUTS 3 areas. Distances are missing for two NUTS 3 regions in Portugal.

[30]The inclusion of distance creates some odd patterns when used with multiple countries as regions that have the same absolute distance to Ischgl will be considered relatively far and relatively close depending on the domestic internal distance. This is since the country fixed effect will capture the the part of the distance that is common to all regions in a country. An example is Netherlands and Denmark who border Germany. Many of these area will have the lowest internal distance while the bordering areas in Germany will have relatively high measure of internal distance since other German areas are closer.

dampened. The large week 10 effect is unchanged. This likely reflects the wide spread testing in Germany from the first initial stages, compared to other countries[31], combined with the fact that week 9 regions in Germany are in the most southern part of the country (relatively closest to Ischgl). Importantly, we see that the results on post-summer persistence are unchanged consistent with the results in figure 9 which shows minimal role of absolute distance. See figure 10 and tables 17 and 18 for the full results.

Third, we may be worried that the results are driven by German regions that are within a few hundred kilometers from the Austrian ski-resorts. Hence, regions were it may be possible to take day-trips to the Alps rather than longer extended periods during the school-breaks. To investigate this potential issue we drop the two regions in Germany that are closest to Austria (Bavaria and Baden-Württemberg). The results are very similar, see figure 11. Fourth, as discussed in footnote 16, Covid-19 had spread to more areas and travel to non-ski related areas may lead to exposure in the later break-weeks (9-10).

Distance is therefore not included in the main specification since: 1) the absolute distance has a no impact on the results suggestive of a dominant role of the timing of travel, 2) the relative internal distance to Ischgl has in general a small and unclear role in our setting given country fixed effects and other controls (e.g. typology), 3) the spread becomes more broad over time resulting in travel in general being likely to lead to exposure and not only travel to Austria.

[31] Anecdotal indications of such bias can be seen from the results for the Netherlands in figure 6, were the the week 9 effect increases over the summer, following a broadening of the testing policy and capturing more cases in high exposed municipalities. The patterns in regards to hospitalizations/deaths, not influenced by the policy change, show however a decrease in the week 9 effect.

5.3 Descriptive Statistics

Table 2: Share of regions in each break-week by country (upper panel) and share of population in each break-week (lower panel).

	Country code													
	AT	BE	DE	DK	EE	FI	IE	LV	NL	NO	PT	SE	SI	SK
<=W7	0.69	0	0.62	0.73	0	0	0	1	0	0	0	0.095	0	0
W8	0.31	0	0.14	0.18	0	0.21	1	0	0.50	0.72	0	0.43	0.33	0.38
W9	0	1	0.24	0.091	1	0.53	0	0	0.50	0.17	1	0.29	0.67	0.38
W10	0	0	0.0025	0	0	0.26	0	0	0	0.11	0	0.19	0	0.25
	Country code													
	AT	BE	DE	DK	EE	FI	IE	LV	NL	NO	PT	SE	SI	SK
<=W7	0.69	0	0.71	0.85	0	0	0	1	0	0	0	0.2	0	0
W8	0.31	0	0.11	0.14	0	0.43	1	0	0.36	0.67	0	0.36	0.47	0.35
W9	0	1	0.16	0.01	1	0.37	0	0	0.64	0.24	1	0.35	0.53	0.35
W10	0	0	0.02	0	0	0.19	0	0	0	0.08	0	0.09	0	0.30
# NUTS 3	35	43	401	11	5	19	8	6	40	18	25	21	12	8

Table 3: Descriptive statistics for all countries

	Week nr.			
	<=7	8	9	10
Population	256054	276688	259177	417512
Median age	46.3	44.6	44.5	43.0
Area (km sq.)	1478	3346	2287	34639
Income	9602	1087	9205	15770
Share over age 60	28.4	27.3	27.0	27.3

Table 4: Degree of area urbanization by school break week (column %)

	Week Nr.				
Deg. of Urbanization	<=7	8	9	10	Total
Cities/Urban	26	22	19	7	23
Predom. Urban	48	46	40	29	44
Rural	26	32	41	64	33

5.4 Results Appendix

5.4.1 Broad Sample Results

Table 5: Baseline results for using a joint dummy (either week 8, 9 or 10).

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break =>W8	0.471^a	0.385^b	0.0549	-0.144	-0.0945	0.167^c	0.295^a	0.266^a	0.377^a	0.276^b
	(0.116)	(0.150)	(0.197)	(0.130)	(0.135)	(0.0950)	(0.106)	(0.0848)	(0.0900)	(0.116)
Population	0.540^a	0.941^a	0.927^a	0.785^a	0.922^a	0.727^a	1.031^a	1.242^a	1.232^a	1.227^a
	(0.127)	(0.179)	(0.203)	(0.230)	(0.221)	(0.138)	(0.123)	(0.0953)	(0.104)	(0.119)
Median age	5.718^a	10.00^a	10.02^a	6.594^a	5.259^b	4.223^a	0.734	-0.301	2.384^b	2.558^c
	(1.343)	(1.505)	(1.670)	(2.473)	(2.271)	(1.424)	(1.563)	(1.264)	(1.189)	(1.333)
Share below 14	-0.167	-0.0914	0.256	1.137^c	1.387^b	0.845^c	1.141^b	0.806^c	0.419	-0.0705
	(0.528)	(0.668)	(0.883)	(0.660)	(0.659)	(0.495)	(0.518)	(0.440)	(0.430)	(0.454)
Share over age 60	-4.608^a	-6.417^a	-5.646^a	-3.358^b	-3.408^b	-3.768^a	-1.526	-0.650	-1.441^c	-0.579
	(0.812)	(0.915)	(1.094)	(1.538)	(1.518)	(0.928)	(0.949)	(0.823)	(0.852)	(1.033)
Area (km sq.)	0.00972	-0.181^a	-0.242^a	-0.290^a	-0.233^a	-0.179^a	-0.221^a	-0.0869^b	-0.114^a	-0.134^a
	(0.0436)	(0.0506)	(0.0613)	(0.0741)	(0.0674)	(0.0421)	(0.0422)	(0.0345)	(0.0308)	(0.0330)
Income	0.518^a	0.327^a	0.310^b	0.429^b	0.304^c	0.454^a	0.240^b	-0.0678	-0.0799	-0.0362
	(0.0943)	(0.121)	(0.153)	(0.178)	(0.162)	(0.105)	(0.105)	(0.0858)	(0.0768)	(0.0896)
Interm. urb.	0.0137	0.0956	-0.0472	-0.149	-0.276^c	-0.194^b	-0.0597	-0.210^a	-0.141^b	-0.0309
	(0.0897)	(0.100)	(0.134)	(0.146)	(0.143)	(0.0827)	(0.0747)	(0.0714)	(0.0577)	(0.0636)
Rural	0.00800	0.344^b	0.0791	-0.0312	-0.173	-0.168	0.0451	-0.118	-0.0652	0.0524
	(0.110)	(0.161)	(0.213)	(0.197)	(0.172)	(0.123)	(0.113)	(0.102)	(0.0900)	(0.0912)
BE	0.190	1.913^a	2.406^a	0.832^b	0.439	0.148	-0.198	0.676^a	-1.271^a	-0.768^a
	(0.258)	(0.285)	(0.383)	(0.338)	(0.275)	(0.183)	(0.229)	(0.209)	(0.174)	(0.181)
DE	0.00694	0.900^a	1.142^a	-0.0277	-0.626^a	-0.163	-1.095^a	-1.043^a	-1.376^a	-0.420^a
	(0.205)	(0.220)	(0.285)	(0.197)	(0.169)	(0.102)	(0.174)	(0.104)	(0.124)	(0.123)
DK	-0.232	1.155^a	1.717^a	0.461	-0.351	-0.215	-0.0675	-1.133^a	-1.369^a	0.291
	(0.257)	(0.323)	(0.411)	(0.403)	(0.320)	(0.326)	(0.208)	(0.140)	(0.178)	(0.182)
EE	3.282^a	5.750^a	7.632^a	6.900^a	4.695^a	5.040^a	4.100^a	1.710^a	1.422^a	2.542^a
	(0.260)	(0.295)	(0.365)	(0.383)	(0.356)	(0.219)	(0.276)	(0.179)	(0.179)	(0.213)
FI	-1.216^a	0.424	1.458^a	-0.301	-1.269^a	-1.130^a	-1.479^a	-2.530^a	-3.005^a	-2.203^a
	(0.296)	(0.328)	(0.450)	(0.440)	(0.405)	(0.216)	(0.307)	(0.208)	(0.246)	(0.312)
IE	-1.047^a	1.970^a	2.633^a	0.207	-1.033^a	-0.656^b	-0.965^a	-1.275^a	-2.813^a	-1.033^a
	(0.311)	(0.395)	(0.580)	(0.414)	(0.333)	(0.268)	(0.309)	(0.257)	(0.229)	(0.241)
LV	-1.310^a	0.100	1.490^a	0.141	-1.053^a	-0.650^a	-1.867^a	-1.369^a	-1.240^a	0.348^c
	(0.224)	(0.261)	(0.371)	(0.332)	(0.310)	(0.196)	(0.240)	(0.160)	(0.172)	(0.186)
NL	-0.972^a	1.573^a	1.461^a	0.255	-0.892^a	-0.126	-0.236	-0.164	-1.395^a	0.326^c
	(0.276)	(0.300)	(0.403)	(0.355)	(0.317)	(0.198)	(0.226)	(0.151)	(0.167)	(0.180)
NO	-1.631^a	0.0757	0.840^c	-0.0736	-1.432^a	-0.878^a	-1.666^a	-2.347^a	-2.467^a	-1.695^a
	(0.305)	(0.316)	(0.479)	(0.374)	(0.367)	(0.255)	(0.271)	(0.210)	(0.239)	(0.361)
PT	-1.029^b	1.202^a	2.344^a	1.931^a	0.950^b	0.452^c	-0.0923	-1.661^a	-3.161^a	-2.047^a
	(0.460)	(0.393)	(0.387)	(0.463)	(0.403)	(0.261)	(0.350)	(0.317)	(0.293)	(0.257)
SE	-0.574^c	2.581^a	4.746^a	4.294^a	1.646^a	0.841^a	-0.473	-1.021^a	-0.446^c	0.733^a
	(0.345)	(0.391)	(0.449)	(0.469)	(0.451)	(0.310)	(0.301)	(0.223)	(0.238)	(0.264)
SI	-0.832^a	-0.402	-0.220	1.169^a	0.466	0.298	-0.0255	0.334^b	-0.237	0.731^a
	(0.308)	(0.361)	(0.333)	(0.315)	(0.282)	(0.213)	(0.284)	(0.134)	(0.177)	(0.213)
SK	-2.446^a	-0.595^c	-0.398	0.0535	-0.416	-0.292	-0.356	-0.388^b	-1.317^a	0.257
	(0.281)	(0.327)	(0.419)	(0.457)	(0.308)	(0.290)	(0.292)	(0.187)	(0.197)	(0.185)
Constant	-12.17^a	-26.40^a	-30.65^a	-25.53^a	-20.87^a	-13.24^a	-8.603^b	-5.331^c	-10.75^a	-14.05^a
	(3.316)	(4.014)	(4.816)	(4.648)	(4.673)	(2.873)	(3.612)	(2.775)	(2.576)	(2.228)
Observations	647	649	649	649	649	649	649	649	649	649

Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$
Same results as in figure 4. Data from two areas is missing in March.

Table 6: Baseline results using separate week specific dummies(w8, w9 and w10)

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break W8	0.273^{a}	0.0810	-0.312^{c}	-0.263^{c}	-0.263^{c}	0.0953	0.0414	0.223^{b}	0.270^{a}	0.235^{c}
	(0.101)	(0.128)	(0.160)	(0.151)	(0.158)	(0.101)	(0.0862)	(0.0998)	(0.100)	(0.135)
Break W9	0.648^{a}	0.658^{a}	0.395^{c}	-0.0362	0.0615	0.233^{b}	0.534^{a}	0.313^{a}	0.475^{a}	0.322^{a}
	(0.122)	(0.147)	(0.221)	(0.132)	(0.130)	(0.111)	(0.0916)	(0.0851)	(0.0857)	(0.110)
Break W10	0.467^{a}	0.667^{a}	-0.0641	-0.0620	-0.130	0.192	0.0823	-0.0577	0.385^{b}	-0.0717
	(0.172)	(0.214)	(0.306)	(0.271)	(0.205)	(0.196)	(0.177)	(0.106)	(0.155)	(0.166)
Population	0.586^{a}	1.101^{a}	1.098^{a}	0.846^{a}	1.001^{a}	0.763^{a}	1.144^{a}	1.248^{a}	1.284^{a}	1.231^{a}
	(0.133)	(0.177)	(0.193)	(0.237)	(0.221)	(0.137)	(0.121)	(0.0970)	(0.104)	(0.113)
Median age	5.100^{a}	9.138^{a}	8.637^{a}	6.235^{b}	4.639^{b}	3.988^{a}	-0.319	-0.692	2.015	2.157
	(1.391)	(1.564)	(1.732)	(2.494)	(2.254)	(1.444)	(1.560)	(1.311)	(1.222)	(1.343)
Share below 14	0.0700	0.267	0.665	1.276^{c}	1.575^{b}	0.928^{c}	1.417^{a}	0.838^{c}	0.540	-0.0422
	(0.502)	(0.605)	(0.811)	(0.651)	(0.637)	(0.486)	(0.494)	(0.445)	(0.429)	(0.453)
Share over age 60	-4.012^{a}	-5.545^{a}	-4.465^{a}	-3.008^{c}	-2.870^{c}	-3.550^{a}	-0.672	-0.426	-1.110	-0.353
	(0.849)	(0.952)	(1.114)	(1.533)	(1.478)	(0.915)	(0.946)	(0.862)	(0.883)	(1.041)
Area (km sq.)	0.00541	-0.212^{a}	-0.258^{a}	-0.301^{a}	-0.242^{a}	-0.184^{a}	-0.226^{a}	-0.0744^{b}	-0.120^{a}	-0.120^{a}
	(0.0434)	(0.0465)	(0.0603)	(0.0769)	(0.0703)	(0.0422)	(0.0404)	(0.0365)	(0.0309)	(0.0332)
Income	0.480^{a}	0.208^{c}	0.174	0.383^{b}	0.241	0.426^{a}	0.148	-0.0786	-0.120	-0.0459
	(0.0994)	(0.119)	(0.143)	(0.183)	(0.162)	(0.106)	(0.102)	(0.0851)	(0.0772)	(0.0862)
Interm. urb.	-0.00215	0.0932	-0.0712	-0.151	-0.286^{b}	-0.197^{b}	-0.0823	-0.227^{a}	-0.146^{b}	-0.0489
	(0.0866)	(0.0956)	(0.127)	(0.146)	(0.137)	(0.0823)	(0.0724)	(0.0712)	(0.0566)	(0.0631)
Rural	-0.0333	0.314^{b}	0.0198	-0.0444	-0.199	-0.177	-0.00258	-0.141	-0.0803	0.0290
	(0.102)	(0.157)	(0.207)	(0.200)	(0.164)	(0.121)	(0.110)	(0.103)	(0.0877)	(0.0913)
BE	-0.130	1.389^{a}	1.777^{a}	0.627^{c}	0.150	0.0241	-0.633^{a}	0.605^{a}	-1.454^{a}	-0.835^{a}
	(0.247)	(0.263)	(0.400)	(0.351)	(0.284)	(0.201)	(0.208)	(0.216)	(0.176)	(0.182)
DE	-0.106	0.700^{a}	0.923^{a}	-0.105	-0.728^{a}	-0.208^{b}	-1.240^{a}	-1.053^{a}	-1.442^{a}	-0.428^{a}
	(0.185)	(0.192)	(0.245)	(0.202)	(0.191)	(0.102)	(0.145)	(0.107)	(0.125)	(0.127)
DK	-0.347	0.974^{a}	1.497^{a}	0.390	-0.452	-0.258	-0.220	-1.160^{a}	-1.432^{a}	0.266
	(0.230)	(0.286)	(0.375)	(0.407)	(0.337)	(0.329)	(0.190)	(0.143)	(0.173)	(0.184)
EE	2.933^{a}	5.180^{a}	6.902^{a}	6.674^{a}	4.362^{a}	4.901^{a}	3.583^{a}	1.596^{a}	1.214^{a}	2.431^{a}
	(0.263)	(0.286)	(0.376)	(0.393)	(0.356)	(0.234)	(0.258)	(0.194)	(0.184)	(0.208)
FI	-1.438^{a}	0.0478	1.074^{b}	-0.444	-1.448^{a}	-1.213^{a}	-1.726^{a}	-2.528^{a}	-3.123^{a}	-2.195^{a}
	(0.289)	(0.315)	(0.480)	(0.443)	(0.390)	(0.211)	(0.306)	(0.199)	(0.255)	(0.291)
IE	-0.942^{a}	2.127^{a}	2.804^{a}	0.267	-0.954^{a}	-0.620^{b}	-0.852^{a}	-1.267^{a}	-2.761^{a}	-1.027^{a}
	(0.286)	(0.356)	(0.523)	(0.412)	(0.353)	(0.269)	(0.266)	(0.249)	(0.224)	(0.243)
LV	-1.482^{a}	-0.216	1.090^{a}	0.0155	-1.237^{a}	-0.727^{a}	-2.150^{a}	-1.428^{a}	-1.355^{a}	0.290
	(0.213)	(0.234)	(0.325)	(0.338)	(0.313)	(0.195)	(0.218)	(0.167)	(0.175)	(0.184)
NL	-1.091^{a}	1.338^{a}	1.190^{a}	0.164	-1.017^{a}	-0.181	-0.421^{b}	-0.188	-1.475^{a}	0.304^{c}
	(0.240)	(0.252)	(0.354)	(0.341)	(0.302)	(0.195)	(0.207)	(0.147)	(0.159)	(0.175)
NO	-1.626^{a}	0.107	0.882^{c}	-0.0613	-1.413^{a}	-0.871^{a}	-1.636^{a}	-2.339^{a}	-2.456^{a}	-1.687^{a}
	(0.286)	(0.289)	(0.452)	(0.379)	(0.373)	(0.252)	(0.239)	(0.208)	(0.249)	(0.355)
PT	-1.329^{a}	0.691^{c}	1.713^{a}	1.730^{a}	0.661	0.329	-0.534	-1.745^{a}	-3.343^{a}	-2.129^{a}
	(0.466)	(0.389)	(0.387)	(0.474)	(0.417)	(0.275)	(0.340)	(0.332)	(0.303)	(0.260)
SE	-0.722^{b}	2.345^{a}	4.493^{a}	4.204^{a}	1.529^{a}	0.788^{b}	-0.639^{b}	-1.028^{a}	-0.522^{b}	0.729^{a}
	(0.339)	(0.373)	(0.423)	(0.459)	(0.435)	(0.303)	(0.271)	(0.225)	(0.243)	(0.268)
SI	-1.007^{a}	-0.717^{a}	-0.603^{c}	1.045^{a}	0.290	0.223	-0.291	0.288^{b}	-0.348^{b}	0.687^{a}
	(0.231)	(0.237)	(0.322)	(0.357)	(0.254)	(0.193)	(0.187)	(0.132)	(0.144)	(0.194)
SK	-2.540^{a}	-0.875^{a}	-0.636	-0.0501	-0.530	-0.350	-0.493^{c}	-0.348^{c}	-1.395^{a}	0.304^{c}
	(0.280)	(0.330)	(0.441)	(0.449)	(0.327)	(0.312)	(0.283)	(0.177)	(0.204)	(0.181)
Constant	-12.49^{a}	-27.45^{a}	-30.93^{a}	-25.88^{a}	-21.04^{a}	-13.40^{a}	-8.515^{b}	-4.701^{c}	-10.92^{a}	-13.36^{a}
	(3.187)	(3.756)	(4.586)	(4.790)	(4.828)	(2.934)	(3.584)	(2.826)	(2.555)	(2.201)
Observations	647	649	649	649	649	649	649	649	649	649

Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$
Same results as in figure 4.

Table 7: Urban/Rural comparison results

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break =>W8	0.390^{a}	0.294^{b}	-0.0947	-0.474^{b}	-0.395^{c}	-0.146	-0.000238	-0.113	0.230^{b}	0.329^{a}
	(0.143)	(0.132)	(0.194)	(0.230)	(0.228)	(0.124)	(0.114)	(0.107)	(0.0952)	(0.0927)
Interm. urb.	-0.0431	0.00669	-0.129	-0.322	-0.477^{b}	-0.335^{a}	-0.221^{b}	-0.413^{a}	-0.227^{a}	-0.0301
	(0.117)	(0.131)	(0.186)	(0.206)	(0.206)	(0.0968)	(0.0896)	(0.0744)	(0.0690)	(0.0833)
Rural	-0.0366	0.335	-0.0494	-0.326	-0.366	-0.489^{a}	-0.208	-0.450^{a}	-0.181	0.148
	(0.145)	(0.252)	(0.335)	(0.260)	(0.234)	(0.138)	(0.139)	(0.126)	(0.120)	(0.128)
break =>W8 × Interm. urb	0.115	0.174	0.165	0.353	0.401^{c}	0.291^{c}	0.328^{a}	0.412^{a}	0.172^{c}	-0.00589
	(0.151)	(0.153)	(0.230)	(0.240)	(0.235)	(0.149)	(0.115)	(0.0954)	(0.0961)	(0.116)
break =>W8 × Rural	0.0896	0.0309	0.234	0.534^{c}	0.367	0.574^{a}	0.461^{a}	0.604^{a}	0.213^{c}	-0.163
	(0.178)	(0.235)	(0.313)	(0.284)	(0.245)	(0.148)	(0.140)	(0.118)	(0.125)	(0.152)
Population	0.538^{a}	0.934^{a}	0.910^{a}	0.748^{a}	0.891^{a}	0.691^{a}	0.999^{a}	1.200^{a}	1.217^{a}	1.235^{a}
	(0.126)	(0.181)	(0.211)	(0.224)	(0.222)	(0.129)	(0.122)	(0.0878)	(0.103)	(0.119)
Median age	5.656^{a}	9.871^{a}	9.991^{a}	6.555^{a}	5.101^{b}	4.255^{a}	0.681	-0.356	2.342^{c}	2.485^{c}
	(1.341)	(1.506)	(1.674)	(2.370)	(2.192)	(1.330)	(1.500)	(1.231)	(1.201)	(1.326)
Share below 14	-0.146	-0.0512	0.285	1.196^{c}	1.465^{b}	0.888^{c}	1.198^{b}	0.877^{c}	0.450	-0.0642
	(0.535)	(0.675)	(0.886)	(0.663)	(0.667)	(0.493)	(0.513)	(0.450)	(0.436)	(0.458)
Share over age 60	-4.565^{a}	-6.348^{a}	-5.596^{a}	-3.254^{b}	-3.271^{b}	-3.693^{a}	-1.427	-0.528	-1.386	-0.568
	(0.821)	(0.913)	(1.088)	(1.477)	(1.470)	(0.867)	(0.905)	(0.816)	(0.866)	(1.017)
Area (km sq.)	0.0122	-0.176^{a}	-0.237^{a}	-0.278^{a}	-0.221^{a}	-0.168^{a}	-0.211^{a}	-0.0734^{b}	-0.108^{a}	-0.135^{a}
	(0.0435)	(0.0511)	(0.0653)	(0.0723)	(0.0663)	(0.0385)	(0.0420)	(0.0334)	(0.0306)	(0.0323)
Income	0.519^{a}	0.331^{a}	0.324^{b}	0.458^{a}	0.327^{b}	0.484^{a}	0.266^{b}	-0.0344	-0.0676	-0.0435
	(0.0939)	(0.122)	(0.158)	(0.174)	(0.164)	(0.102)	(0.103)	(0.0786)	(0.0768)	(0.0914)
BE	0.194	1.926^{a}	2.410^{a}	0.839^{b}	0.457^{c}	0.148	-0.191	0.685^{a}	-1.265^{a}	-0.761^{a}
	(0.257)	(0.278)	(0.389)	(0.331)	(0.269)	(0.180)	(0.232)	(0.203)	(0.174)	(0.176)
DE	0.0119	0.925^{a}	1.136^{a}	-0.0477	-0.614^{a}	-0.199^{c}	-1.108^{a}	-1.063^{a}	-1.379^{a}	-0.397^{a}
	(0.207)	(0.217)	(0.304)	(0.203)	(0.167)	(0.115)	(0.192)	(0.120)	(0.127)	(0.118)
DK	-0.237	1.163^{a}	1.694^{a}	0.408	-0.376	-0.278	-0.112	-1.192^{a}	-1.387^{a}	0.314^{c}
	(0.257)	(0.315)	(0.420)	(0.392)	(0.326)	(0.356)	(0.221)	(0.165)	(0.180)	(0.180)
EE	3.280^{a}	5.770^{a}	7.619^{a}	6.869^{a}	4.696^{a}	4.994^{a}	4.077^{a}	1.676^{a}	1.414^{a}	2.566^{a}
	(0.263)	(0.288)	(0.379)	(0.379)	(0.342)	(0.212)	(0.277)	(0.182)	(0.185)	(0.205)
FI	-1.231^{a}	0.423	1.411^{a}	-0.408	-1.336^{a}	-1.248^{a}	-1.570^{a}	-2.650^{a}	-3.046^{a}	-2.167^{a}
	(0.307)	(0.334)	(0.477)	(0.446)	(0.388)	(0.212)	(0.311)	(0.226)	(0.259)	(0.301)
IE	-1.051^{a}	1.983^{a}	2.612^{a}	0.157	-1.051^{a}	-0.718^{b}	-1.006^{a}	-1.330^{a}	-2.829^{a}	-1.008^{a}
	(0.312)	(0.395)	(0.590)	(0.404)	(0.330)	(0.279)	(0.299)	(0.239)	(0.226)	(0.248)
LV	-1.309^{a}	0.111	1.497^{a}	0.155	-1.033^{a}	-0.640^{a}	-1.853^{a}	-1.352^{a}	-1.232^{a}	0.350^{c}
	(0.225)	(0.256)	(0.377)	(0.325)	(0.305)	(0.193)	(0.244)	(0.165)	(0.175)	(0.185)
NL	-0.955^{a}	1.597^{a}	1.493^{a}	0.323	-0.825^{b}	-0.0642	-0.174	-0.0852	-1.364^{a}	0.318^{c}
	(0.274)	(0.294)	(0.408)	(0.357)	(0.329)	(0.206)	(0.239)	(0.164)	(0.169)	(0.171)
NO	-1.643^{a}	0.0691	0.806	-0.151	-1.487^{a}	-0.960^{a}	-1.734^{a}	-2.435^{a}	-2.499^{a}	-1.673^{a}
	(0.309)	(0.319)	(0.500)	(0.388)	(0.349)	(0.242)	(0.282)	(0.218)	(0.252)	(0.355)
PT	-1.028^{b}	1.231^{a}	2.330^{a}	1.893^{a}	0.956^{b}	0.393	-0.120	-1.702^{a}	-3.170^{a}	-2.015^{a}
	(0.465)	(0.390)	(0.401)	(0.452)	(0.392)	(0.259)	(0.356)	(0.332)	(0.301)	(0.252)
SE	-0.596^{c}	2.555^{a}	4.705^{a}	4.204^{a}	1.562^{a}	0.757^{b}	-0.554^{c}	-1.124^{a}	-0.486^{c}	0.746^{a}
	(0.351)	(0.392)	(0.468)	(0.464)	(0.434)	(0.293)	(0.304)	(0.231)	(0.248)	(0.265)
SI	-0.838^{a}	-0.380	-0.247	1.104^{a}	0.447	0.213	-0.0777	0.263^{c}	-0.257	0.768^{a}
	(0.315)	(0.370)	(0.353)	(0.325)	(0.281)	(0.199)	(0.288)	(0.142)	(0.181)	(0.220)
SK	-2.450^{a}	-0.587^{c}	-0.399	0.0493	-0.410	-0.302	-0.359	-0.392^{b}	-1.316^{a}	0.264
	(0.285)	(0.324)	(0.425)	(0.455)	(0.307)	(0.300)	(0.301)	(0.179)	(0.195)	(0.179)
Constant	-12.10^{a}	-26.20^{a}	-30.66^{a}	-25.60^{a}	-20.69^{a}	-13.44^{a}	-8.628^{b}	-5.388^{b}	-10.73^{a}	-13.89^{a}
	(3.309)	(4.041)	(4.918)	(4.623)	(4.739)	(2.689)	(3.541)	(2.672)	(2.529)	(2.255)
Observations	647	649	649	649	649	649	649	649	649	649

Standard errors in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$

Same results as in figures 7

5.4.2 Country Specific Results

Table 8: Germany only - Nr. cases on LHS: Results using joint week dummy(w8+).

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break =>W8	0.557^a	0.451^a	0.105	-0.231^c	-0.172	0.145^c	0.347^a	0.323^a	0.445^a	0.329^b
	(0.123)	(0.162)	(0.217)	(0.136)	(0.124)	(0.0841)	(0.103)	(0.0914)	(0.100)	(0.127)
Population	0.765^a	0.970^a	1.081^a	1.016^a	1.260^a	0.917^a	1.180^a	1.318^a	1.197^a	1.122^a
	(0.178)	(0.202)	(0.252)	(0.307)	(0.252)	(0.140)	(0.131)	(0.107)	(0.106)	(0.144)
Median age	4.715^b	11.50^a	12.85^a	12.77^a	12.75^a	7.932^a	3.853^c	3.331^c	3.314^b	0.201
	(1.765)	(2.252)	(2.857)	(2.810)	(3.079)	(1.767)	(2.096)	(1.833)	(1.562)	(2.019)
Share over age 60	-4.626^a	-7.440^a	-7.844^a	-7.350^a	-8.389^a	-6.343^a	-3.227^b	-2.205^b	-1.244	1.509
	(0.967)	(1.220)	(1.838)	(1.630)	(1.885)	(1.071)	(1.263)	(1.030)	(1.018)	(1.453)
Share below 14	-0.0610	-0.0895	-0.198	0.101	0.214	1.047	1.939^a	0.931	1.221^b	0.769
	(0.662)	(0.964)	(1.467)	(0.993)	(0.979)	(0.689)	(0.643)	(0.611)	(0.585)	(0.620)
Area (km sq.)	0.00245	-0.225^a	-0.325^a	-0.439^a	-0.413^a	-0.300^a	-0.341^a	-0.186^a	-0.163^a	-0.0852^c
	(0.0568)	(0.0645)	(0.0870)	(0.110)	(0.101)	(0.0456)	(0.0564)	(0.0534)	(0.0466)	(0.0502)
Income	0.336^a	0.335^b	0.256	0.321	0.158	0.304^a	0.223^c	0.0181	0.0472	0.0498
	(0.117)	(0.134)	(0.203)	(0.246)	(0.174)	(0.100)	(0.123)	(0.101)	(0.0823)	(0.111)
Interm. urb.	0.120	0.219^b	0.134	-0.0315	-0.0563	-0.122	0.103	-0.107	-0.100	-0.0848
	(0.111)	(0.105)	(0.165)	(0.181)	(0.168)	(0.0937)	(0.0832)	(0.0909)	(0.0668)	(0.0765)
Rural	0.0754	0.423^b	0.282	0.0536	0.00557	-0.0858	0.249^c	-0.0556	-0.0262	0.0470
	(0.125)	(0.183)	(0.255)	(0.257)	(0.215)	(0.138)	(0.125)	(0.120)	(0.110)	(0.117)
Constant	-9.715^b	-28.09^a	-32.86^a	-34.19^a	-32.32^a	-19.80^a	-19.06^a	-16.55^a	-18.82^a	-14.19^a
	(3.989)	(5.451)	(6.107)	(5.612)	(6.895)	(3.228)	(4.656)	(4.049)	(3.937)	(3.522)
Observations	401	401	401	401	401	401	401	401	401	401

Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$
Same results as in figure 5.

Table 9: Germany only - Nr. cases on LHS: Results using separate week specific dummies(w8, w9/w10 grouped).

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break W8	0.337^a	0.0723	-0.322	-0.332^c	-0.329^c	0.138	0.0342	0.304^b	0.356^a	0.229
	(0.104)	(0.151)	(0.218)	(0.165)	(0.178)	(0.0941)	(0.0933)	(0.143)	(0.126)	(0.163)
Break W9/W10	0.736^a	0.758^a	0.452^c	-0.149	-0.0442	0.151	0.601^a	0.339^a	0.517^a	0.411^a
	(0.149)	(0.175)	(0.263)	(0.136)	(0.146)	(0.116)	(0.0917)	(0.0970)	(0.0923)	(0.118)
Population	0.879^a	1.165^a	1.302^a	1.068^a	1.341^a	0.921^a	1.342^a	1.328^a	1.243^a	1.174^a
	(0.195)	(0.201)	(0.238)	(0.319)	(0.254)	(0.140)	(0.130)	(0.112)	(0.106)	(0.132)
Median age	3.767^b	9.875^a	11.01^a	12.34^a	12.07^a	7.902^a	2.507	3.248^c	2.931^c	-0.230
	(1.767)	(2.250)	(2.819)	(2.715)	(2.977)	(1.818)	(1.855)	(1.920)	(1.573)	(2.065)
Share over age 60	-3.756^a	-5.946^a	-6.156^a	-6.951^a	-7.768^a	-6.316^a	-1.992^c	-2.129^c	-0.892	1.904
	(1.040)	(1.317)	(1.929)	(1.583)	(1.889)	(1.126)	(1.124)	(1.107)	(1.039)	(1.511)
Share below 14	0.159	0.288	0.228	0.202	0.371	1.054	2.251^a	0.950	1.310^b	0.869
	(0.649)	(0.890)	(1.387)	(0.974)	(0.933)	(0.699)	(0.516)	(0.597)	(0.574)	(0.619)
Area (km sq.)	-0.00814	-0.243^a	-0.346^a	-0.444^a	-0.421^a	-0.301^a	-0.356^a	-0.187^a	-0.168^a	-0.0901^c
	(0.0557)	(0.0528)	(0.0783)	(0.109)	(0.0999)	(0.0453)	(0.0478)	(0.0521)	(0.0446)	(0.0485)
Income	0.254^c	0.196	0.0979	0.284	0.100	0.301^a	0.107	0.0110	0.0143	0.0128
	(0.132)	(0.129)	(0.189)	(0.256)	(0.174)	(0.103)	(0.119)	(0.100)	(0.0867)	(0.106)
Interm. urb.	0.0954	0.177^c	0.0869	-0.0426	-0.0736	-0.122	0.0683	-0.109	-0.110	-0.0958
	(0.106)	(0.105)	(0.159)	(0.183)	(0.160)	(0.0953)	(0.0899)	(0.0893)	(0.0684)	(0.0818)
Rural	0.0446	0.370^c	0.223	0.0395	-0.0164	-0.0867	0.205	-0.0583	-0.0387	0.0330
	(0.112)	(0.184)	(0.253)	(0.261)	(0.205)	(0.141)	(0.130)	(0.120)	(0.109)	(0.119)
Constant	-10.15^a	-28.82^a	-33.70^a	-34.38^a	-32.63^a	-19.82^a	-19.68^a	-16.58^a	-18.99^a	-14.39^a
	(3.689)	(4.928)	(5.609)	(5.620)	(6.870)	(3.214)	(4.546)	(4.010)	(3.840)	(3.425)
Observations	401	401	401	401	401	401	401	401	401	401

Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$
Same results as in figure 5.

Table 10: Germany only - Nr. Deaths on LHS: Results using separate week specific dummies(w8, w9/w10 grouped).

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break W8	-0.0371	-0.0512	-0.123	-0.110^b	-0.133^a	-0.0587	0.0633	0.313	0.539^a	0.204
	(0.152)	(0.139)	(0.0998)	(0.0472)	(0.0422)	(0.0498)	(0.0863)	(0.196)	(0.190)	(0.191)
Break W9/W10	0.740^a	0.696^a	0.210	-0.0267	-0.0439	-0.0189	0.0642	0.327^b	0.608^a	0.349^b
	(0.159)	(0.159)	(0.135)	(0.0598)	(0.0363)	(0.0499)	(0.0679)	(0.128)	(0.141)	(0.158)
Population	0.542	0.748^a	0.329^c	0.0536	0.489^a	0.345^a	0.388^a	1.212^a	1.256^a	1.270^a
	(0.323)	(0.249)	(0.173)	(0.154)	(0.118)	(0.105)	(0.127)	(0.227)	(0.183)	(0.217)
Median age	3.405	8.035^a	5.850^a	3.103^a	2.925^a	2.537^a	3.273^b	3.201	0.818	3.218
	(2.618)	(2.713)	(1.573)	(0.993)	(0.826)	(0.797)	(1.368)	(2.680)	(2.323)	(2.652)
Share over age 60	-2.858^c	-4.097^b	-2.068^c	-1.392^b	-1.593^a	-1.236^a	-1.252	0.509	1.241	0.568
	(1.521)	(1.524)	(1.122)	(0.594)	(0.546)	(0.441)	(0.908)	(1.697)	(1.626)	(1.958)
Share below 14	0.131	0.0252	-0.164	-0.471	-0.541	-0.323	0.253	2.430^b	1.747^c	-0.541
	(0.970)	(1.008)	(0.623)	(0.403)	(0.343)	(0.299)	(0.545)	(1.097)	(0.901)	(1.012)
Area (km sq.)	0.0161	-0.171^b	-0.115^c	-0.0916^c	-0.143^a	-0.133^a	-0.125^a	-0.231^a	-0.166^b	-0.169^b
	(0.0706)	(0.0782)	(0.0668)	(0.0485)	(0.0339)	(0.0363)	(0.0442)	(0.0735)	(0.0681)	(0.0663)
Income	0.440^c	0.356^c	0.257^b	0.259^b	-0.142^c	-0.0550	0.137^c	0.0976	-0.104	-0.0994
	(0.255)	(0.188)	(0.121)	(0.102)	(0.0766)	(0.0699)	(0.0776)	(0.190)	(0.151)	(0.194)
Interm. urb.	0.0811	0.171	-0.0235	-0.0282	0.0134	0.00177	0.0201	-0.0712	-0.209	-0.115
	(0.162)	(0.142)	(0.0708)	(0.0728)	(0.0491)	(0.0571)	(0.0740)	(0.152)	(0.134)	(0.117)
Rural	0.0221	0.358^c	0.0786	0.00410	0.108	0.0671	0.0730	0.0843	-0.0169	0.119
	(0.194)	(0.210)	(0.118)	(0.105)	(0.0669)	(0.0760)	(0.0974)	(0.186)	(0.188)	(0.154)
Constant	-12.50^b	-26.79^a	-20.08^a	-8.093^a	-8.069^a	-7.441^a	-13.76^a	-32.50^a	-22.23^a	-22.94^a
	(5.356)	(6.888)	(3.484)	(2.649)	(2.149)	(2.463)	(3.183)	(5.816)	(5.225)	(4.637)
Observations	401	401	401	401	401	401	401	401	401	401

Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$
Same results as in figure 5.

Table 11: Germany only - Nr. deaths on LHS: Results using joint week dummy(w8+).

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break =>W8	0.395^b	0.364^b	0.0668	-0.0542	-0.0749^b	-0.0306	0.0630	0.285^c	0.556^a	0.303^b
	(0.161)	(0.157)	(0.107)	(0.0479)	(0.0310)	(0.0422)	(0.0657)	(0.141)	(0.149)	(0.146)
Population	0.296	0.505^b	0.217	0.0141	0.446^a	0.322^a	0.386^a	1.250^a	1.269^a	1.217^a
	(0.298)	(0.240)	(0.172)	(0.152)	(0.112)	(0.0994)	(0.129)	(0.228)	(0.187)	(0.226)
Median age	4.290^c	8.759^a	5.674^a	2.321^b	2.408^a	1.987^b	2.653^b	4.630^c	1.480	1.850
	(2.370)	(2.562)	(1.482)	(0.908)	(0.754)	(0.739)	(1.249)	(2.481)	(2.041)	(1.931)
Percentage above age 60	-0.137^a	-0.174^a	-0.0743^b	-0.0289^c	-0.0399^a	-0.0290^b	-0.0361	-0.0461	0.00278	0.0500
	(0.0448)	(0.0495)	(0.0336)	(0.0147)	(0.0126)	(0.0116)	(0.0252)	(0.0521)	(0.0457)	(0.0421)
Area (km sq.)	0.0479	-0.140^c	-0.0963	-0.0830^c	-0.141^a	-0.128^a	-0.109^b	-0.203^b	-0.136^c	-0.149^b
	(0.0763)	(0.0793)	(0.0660)	(0.0487)	(0.0352)	(0.0352)	(0.0437)	(0.0797)	(0.0682)	(0.0644)
Income	0.612^a	0.527^a	0.331^b	0.281^a	-0.114	-0.0423	0.130	0.0683	-0.122	-0.0789
	(0.224)	(0.189)	(0.129)	(0.102)	(0.0716)	(0.0666)	(0.0812)	(0.196)	(0.146)	(0.201)
Interm. urb.	0.120	0.209	-0.0127	-0.0315	0.0162	-0.000963	0.00654	-0.0815	-0.222	-0.128
	(0.170)	(0.152)	(0.0700)	(0.0720)	(0.0494)	(0.0550)	(0.0758)	(0.160)	(0.141)	(0.118)
Rural	0.0772	0.414^c	0.0995	0.0103	0.123^c	0.0705	0.0526	0.0275	-0.0631	0.117
	(0.216)	(0.217)	(0.113)	(0.104)	(0.0676)	(0.0730)	(0.0994)	(0.196)	(0.194)	(0.160)
Constant	-19.96^b	-36.98^a	-24.03^a	-9.904^a	-11.42^a	-9.338^a	-13.90^a	-29.06^a	-16.36^b	-18.28^a
	(7.853)	(8.589)	(5.048)	(3.403)	(2.781)	(2.792)	(4.213)	(8.237)	(6.670)	(6.301)
Observations	401	401	401	401	401	401	401	401	401	401

Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$
Same results as in figure 5.

Table 12: Netherlands only - Nr. cases on LHS: Results using w9 dummy (w8 is control group).

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break W9	0.472^b	0.353	0.839^a	0.759^a	0.790^a	0.598^a	0.423^a	0.158	0.254	0.151
	(0.228)	(0.229)	(0.231)	(0.178)	(0.209)	(0.163)	(0.112)	(0.174)	(0.220)	(0.180)
Population	0.863^a	0.949^a	0.857^a	0.848^a	0.983^a	1.092^a	1.110^a	1.124^a	1.167^a	1.050^a
	(0.0494)	(0.0510)	(0.118)	(0.153)	(0.148)	(0.128)	(0.0787)	(0.0495)	(0.0641)	(0.0704)
Area (km sq.)	0.0429	0.0336	0.0420	-0.0333	-0.241^b	-0.159^c	-0.0831	-0.115^b	-0.0949^c	-0.0474
	(0.0664)	(0.0579)	(0.0705)	(0.0917)	(0.0936)	(0.0834)	(0.0549)	(0.0450)	(0.0484)	(0.0400)
Median age	8.480^b	11.88^b	4.957	5.591	-13.87^b	-4.158	-2.447	4.243	6.298^b	3.727
	(4.185)	(4.536)	(6.080)	(4.833)	(6.433)	(4.114)	(3.431)	(3.477)	(2.784)	(2.614)
Share over age 60	-0.158^c	-0.229^b	-0.167	-0.177^c	0.210	0.0542	-0.0435	-0.139	-0.159^a	-0.0938^c
	(0.0827)	(0.102)	(0.136)	(0.0998)	(0.126)	(0.0844)	(0.0845)	(0.0851)	(0.0571)	(0.0517)
Income	0.863^c	0.818	0.123	0.0627	-0.0495	0.474	0.105	0.279	0.158	-0.0522
	(0.433)	(0.555)	(0.717)	(0.440)	(0.391)	(0.322)	(0.218)	(0.295)	(0.248)	(0.198)
Interm. urb.	0.0240	0.000238	-0.161	-0.326^c	-0.287	-0.314^c	-0.219^c	0.0499	0.177^b	0.221^b
	(0.0714)	(0.0907)	(0.165)	(0.173)	(0.220)	(0.156)	(0.120)	(0.0732)	(0.0801)	(0.0837)
Rural	-0.114	-0.149	-0.198	-0.319	0.110	-0.453^c	-0.281	0.108	0.135	0.0584
	(0.131)	(0.163)	(0.209)	(0.228)	(0.264)	(0.228)	(0.167)	(0.117)	(0.102)	(0.104)
Constant	-43.52^b	-54.60^a	-23.90	-24.10	42.52^c	3.229	2.929	-19.13	-26.52^b	-15.18
	(16.41)	(16.91)	(21.56)	(17.49)	(23.05)	(14.72)	(10.54)	(11.64)	(10.70)	(10.02)
Observations	351	351	351	351	351	351	351	351	351	351

Standard errors, clustered at NUTS 3 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$

Table 13: Netherlands only - Nr. deaths on LHS: Results using w9 dummy (w8 is control group).

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break W9	0.355	0.533^{b}	0.213^{c}	0.119^{c}	-0.0404	0.0153	-0.0335	0.127	0.185	0.181
	(0.230)	(0.203)	(0.106)	(0.0618)	(0.0451)	(0.0419)	(0.126)	(0.148)	(0.182)	(0.191)
Population	0.535^{a}	0.657^{a}	0.588^{a}	0.287^{a}	0.0677	0.181^{a}	0.239^{a}	0.598^{a}	0.673^{a}	0.736^{a}
	(0.110)	(0.102)	(0.116)	(0.0861)	(0.0551)	(0.0573)	(0.0642)	(0.106)	(0.0958)	(0.0964)
Area (km sq.)	0.103	0.0738	-0.0501	-0.0373	-0.0174	-0.0175	-0.00498	-0.0246	0.0109	-0.0493
	(0.0954)	(0.0568)	(0.0517)	(0.0482)	(0.0264)	(0.0231)	(0.0370)	(0.0605)	(0.0755)	(0.0682)
Median age	14.68^{b}	14.18^{a}	4.618	0.126	1.692	0.0343	2.197	0.372	3.510	-4.733
	(5.879)	(4.468)	(3.634)	(2.050)	(1.020)	(1.100)	(2.472)	(4.045)	(3.633)	(3.552)
Share over age 60	-0.246^{b}	-0.291^{a}	-0.0865	-0.0110	-0.0316	-0.0141	-0.0815	-0.0534	-0.115	0.0861
	(0.112)	(0.0935)	(0.0796)	(0.0475)	(0.0213)	(0.0230)	(0.0519)	(0.0907)	(0.0761)	(0.0803)
Income	0.827^{c}	0.580	0.296	-0.0313	0.0801	0.0268	-0.207	-0.102	0.0931	-0.0142
	(0.489)	(0.535)	(0.220)	(0.166)	(0.0946)	(0.0793)	(0.143)	(0.281)	(0.288)	(0.299)
Interm. urb.	-0.189	-0.267^{b}	-0.189	-0.00130	-0.0463	-0.0574	-0.0633	-0.251^{c}	-0.338^{b}	-0.0906
	(0.152)	(0.112)	(0.161)	(0.111)	(0.0685)	(0.0516)	(0.0709)	(0.142)	(0.164)	(0.154)
Rural	-0.368^{c}	-0.334^{b}	0.0312	0.125	-0.0263	-0.00734	-0.0526	-0.224	-0.315	-0.222
	(0.199)	(0.149)	(0.188)	(0.152)	(0.0983)	(0.0616)	(0.0943)	(0.184)	(0.207)	(0.177)
Constant	-63.77^{a}	-58.68^{a}	-22.87^{c}	-2.073	-6.653^{c}	-1.488	-6.137	-3.664	-17.05	10.33
	(22.78)	(17.60)	(11.94)	(6.815)	(3.852)	(3.995)	(8.018)	(13.20)	(12.72)	(12.36)
Observations	351	351	351	351	351	351	351	351	351	351

Standard errors, clustered at NUTS 3 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$

Table 14: Netherlands only - Nr. hospitalizations on LHS: Results using w9 dummy (w8 is control group).

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break W9	0.372	0.404^{b}	0.509^{a}	0.145^{a}	0.0853^{c}	0.0128	0.145	0.347^{b}	0.335^{b}	0.0308
	(0.228)	(0.186)	(0.162)	(0.0521)	(0.0506)	(0.0545)	(0.117)	(0.154)	(0.146)	(0.138)
Population	0.789^{a}	0.633^{a}	0.377^{a}	0.255^{a}	0.206^{a}	0.309^{a}	0.473^{a}	0.777^{a}	0.797^{a}	0.805^{a}
	(0.0713)	(0.0972)	(0.108)	(0.0774)	(0.0674)	(0.0956)	(0.111)	(0.132)	(0.120)	(0.0939)
Area (km sq.)	0.0331	0.131^{b}	0.0663	-0.0337	-0.00181	-0.0420	-0.0263	-0.00837	-0.0151	-0.0147
	(0.0855)	(0.0629)	(0.0687)	(0.0365)	(0.0376)	(0.0327)	(0.0528)	(0.0549)	(0.0879)	(0.0477)
Median age	15.80^{a}	9.104	-2.680	0.158	1.792	1.858	0.851	7.014^{c}	-2.782	0.0922
	(4.054)	(5.645)	(5.755)	(2.062)	(1.520)	(2.062)	(2.639)	(3.637)	(4.828)	(2.929)
Share over age 60	-0.297^{a}	-0.157	0.0410	-0.0186	-0.0533	-0.0555	-0.0742	-0.193^{a}	0.0106	0.00591
	(0.0870)	(0.123)	(0.116)	(0.0422)	(0.0321)	(0.0416)	(0.0511)	(0.0683)	(0.0977)	(0.0650)
Income	0.993^{b}	0.843^{c}	0.0513	0.00602	-0.0494	0.249^{b}	-0.126	-0.00768	0.0675	0.247
	(0.484)	(0.498)	(0.342)	(0.102)	(0.0882)	(0.0960)	(0.254)	(0.283)	(0.272)	(0.241)
Interm. urb.	-0.00720	-0.256^{b}	-0.171	-0.00692	-0.0833	-0.227^{b}	-0.204	-0.307^{c}	-0.148	-0.165
	(0.113)	(0.123)	(0.121)	(0.0685)	(0.0604)	(0.0840)	(0.129)	(0.155)	(0.141)	(0.111)
Rural	-0.0539	-0.580^{a}	-0.272^{c}	0.119	0.0237	-0.113	-0.129	-0.216	-0.0166	-0.240^{c}
	(0.149)	(0.142)	(0.145)	(0.107)	(0.0813)	(0.107)	(0.161)	(0.177)	(0.184)	(0.137)
Constant	-68.76^{a}	-46.20^{b}	3.733	-2.178	-6.869	-10.29	-3.972	-27.90^{c}	2.708	-9.525
	(16.02)	(20.12)	(19.79)	(7.075)	(5.111)	(6.831)	(10.46)	(14.35)	(16.66)	(9.972)
Observations	351	351	351	351	351	351	351	351	351	351

Standard errors, clustered at NUTS 3 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$

5.5 Broad Results Robustness

Table 15: Robustness results using a joint late dummy. Classification of Mecklenburg-Vorpommern changed (see appendix 5.2)

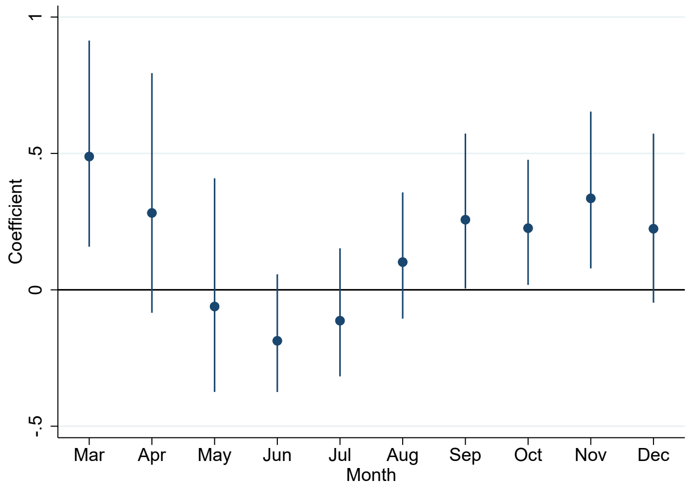
	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break =>W8	0.398^{a}	0.248	-0.0630	-0.207	-0.120	0.0969	0.229^{b}	0.204^{b}	0.289^{a}	0.202
	(0.127)	(0.170)	(0.205)	(0.132)	(0.132)	(0.105)	(0.113)	(0.0938)	(0.108)	(0.126)
Population	0.514^{a}	0.892^{a}	0.898^{a}	0.778^{a}	0.921^{a}	0.703^{a}	1.001^{a}	1.214^{a}	1.194^{a}	1.197^{a}
	(0.128)	(0.197)	(0.216)	(0.228)	(0.220)	(0.141)	(0.128)	(0.105)	(0.120)	(0.130)
Median age	5.883^{a}	10.29^{a}	10.23^{a}	6.685^{a}	5.291^{b}	4.367^{a}	0.887	-0.159	2.585^{b}	2.721^{c}
	(1.333)	(1.547)	(1.686)	(2.448)	(2.248)	(1.389)	(1.538)	(1.269)	(1.236)	(1.400)
Share below 14	-0.223	-0.193	0.163	1.084	1.364^{b}	0.792	1.094^{b}	0.762^{c}	0.357	-0.124
	(0.535)	(0.694)	(0.916)	(0.667)	(0.655)	(0.495)	(0.521)	(0.449)	(0.442)	(0.460)
Share over age 60	-4.792^{a}	-6.692^{a}	-5.841^{a}	-3.436^{b}	-3.433^{b}	-3.905^{a}	-1.677^{c}	-0.789	-1.636^{c}	-0.737
	(0.819)	(0.997)	(1.141)	(1.520)	(1.497)	(0.912)	(0.953)	(0.853)	(0.928)	(1.094)
Area (km sq.)	0.00767	-0.182^{a}	-0.244^{a}	-0.292^{a}	-0.234^{a}	-0.179^{a}	-0.222^{a}	-0.0873^{b}	-0.114^{a}	-0.134^{a}
	(0.0438)	(0.0498)	(0.0606)	(0.0733)	(0.0676)	(0.0418)	(0.0417)	(0.0337)	(0.0301)	(0.0327)
Income	0.526^{a}	0.352^{a}	0.325^{b}	0.433^{b}	0.305^{c}	0.466^{a}	0.254^{b}	-0.0545	-0.0612	-0.0215
	(0.0931)	(0.124)	(0.157)	(0.177)	(0.161)	(0.106)	(0.104)	(0.0872)	(0.0808)	(0.0923)
Interm. urb.	0.0115	0.0969	-0.0413	-0.143	-0.273^{c}	-0.193^{b}	-0.0609	-0.211^{a}	-0.143^{b}	-0.0314
	(0.0895)	(0.0999)	(0.133)	(0.146)	(0.143)	(0.0812)	(0.0732)	(0.0700)	(0.0577)	(0.0660)
Rural	-0.00268	0.344^{b}	0.0953	-0.0128	-0.163	-0.166	0.0392	-0.123	-0.0723	0.0488
	(0.113)	(0.161)	(0.204)	(0.194)	(0.174)	(0.122)	(0.115)	(0.103)	(0.0916)	(0.0947)
BE	0.250	2.035^{a}	2.514^{a}	0.891^{b}	0.463^{c}	0.211	-0.140	0.731^{a}	-1.194^{a}	-0.703^{a}
	(0.247)	(0.277)	(0.375)	(0.342)	(0.273)	(0.185)	(0.223)	(0.211)	(0.181)	(0.190)
DE	0.00385	0.910^{a}	1.157^{a}	-0.0160	-0.621^{a}	-0.158	-1.093^{a}	-1.040^{a}	-1.373^{a}	-0.416^{a}
	(0.195)	(0.202)	(0.273)	(0.200)	(0.171)	(0.0998)	(0.165)	(0.0988)	(0.119)	(0.121)
DK	-0.207	1.196^{a}	1.748^{a}	0.476	-0.346	-0.195	-0.0466	-1.114^{a}	-1.341^{a}	0.313^{c}
	(0.244)	(0.311)	(0.405)	(0.407)	(0.321)	(0.330)	(0.204)	(0.143)	(0.175)	(0.183)
EE	3.366^{a}	5.909^{a}	7.759^{a}	6.963^{a}	4.719^{a}	5.121^{a}	4.181^{a}	1.785^{a}	1.528^{a}	2.629^{a}
	(0.260)	(0.313)	(0.369)	(0.381)	(0.350)	(0.223)	(0.272)	(0.189)	(0.205)	(0.236)
FI	-1.127^{a}	0.575^{c}	1.583^{a}	-0.238	-1.244^{a}	-1.053^{a}	-1.403^{a}	-2.459^{a}	-2.906^{a}	-2.120^{a}
	(0.297)	(0.338)	(0.450)	(0.437)	(0.399)	(0.219)	(0.305)	(0.215)	(0.265)	(0.323)
IE	-0.980^{a}	2.103^{a}	2.749^{a}	0.270	-1.008^{a}	-0.587^{b}	-0.901^{a}	-1.215^{a}	-2.728^{a}	-0.962^{a}
	(0.309)	(0.398)	(0.584)	(0.419)	(0.333)	(0.272)	(0.310)	(0.265)	(0.239)	(0.247)
LV	-1.300^{a}	0.126	1.503^{a}	0.142	-1.054^{a}	-0.638^{a}	-1.851^{a}	-1.355^{a}	-1.220^{a}	0.364^{c}
	(0.214)	(0.252)	(0.367)	(0.330)	(0.310)	(0.194)	(0.233)	(0.160)	(0.176)	(0.193)
NL	-0.916^{a}	1.704^{a}	1.576^{a}	0.318	-0.866^{a}	-0.0586	-0.173	-0.105	-1.312^{a}	0.396^{b}
	(0.267)	(0.294)	(0.396)	(0.358)	(0.315)	(0.199)	(0.221)	(0.155)	(0.178)	(0.190)
NO	-1.566^{a}	0.195	0.948^{b}	-0.0131	-1.407^{a}	-0.816^{a}	-1.610^{a}	-2.294^{a}	-2.394^{a}	-1.633^{a}
	(0.301)	(0.304)	(0.471)	(0.375)	(0.368)	(0.257)	(0.266)	(0.210)	(0.239)	(0.362)
PT	-0.954^{b}	1.340^{a}	2.451^{a}	1.980^{a}	0.969^{b}	0.521^{c}	-0.0204	-1.594^{a}	-3.067^{a}	-1.970^{a}
	(0.457)	(0.406)	(0.388)	(0.461)	(0.398)	(0.265)	(0.346)	(0.320)	(0.306)	(0.271)
SE	-0.490	2.730^{a}	4.872^{a}	4.360^{a}	1.673^{a}	0.917^{a}	-0.400	-0.953^{a}	-0.350	0.813^{a}
	(0.346)	(0.397)	(0.447)	(0.468)	(0.447)	(0.308)	(0.298)	(0.228)	(0.254)	(0.279)
SI	-0.770^{b}	-0.280	-0.121	1.218^{a}	0.484^{c}	0.360^{c}	0.0358	0.391^{a}	-0.157	0.798^{a}
	(0.300)	(0.359)	(0.327)	(0.318)	(0.278)	(0.215)	(0.278)	(0.140)	(0.188)	(0.222)
SK	-2.372^{a}	-0.448	-0.281	0.110	-0.394	-0.218	-0.281	-0.318	-1.218^{a}	0.339
	(0.280)	(0.343)	(0.417)	(0.458)	(0.305)	(0.294)	(0.288)	(0.196)	(0.215)	(0.206)
Constant	-11.77^{a}	-25.89^{a}	-30.32^{a}	-25.42^{a}	-20.84^{a}	-12.99^{a}	-8.310^{b}	-5.062^{c}	-10.37^{a}	-13.74^{a}
	(3.327)	(4.126)	(4.953)	(4.646)	(4.681)	(2.890)	(3.651)	(2.765)	(2.573)	(2.173)
Observations	647	649	649	649	649	649	649	649	649	649

Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$

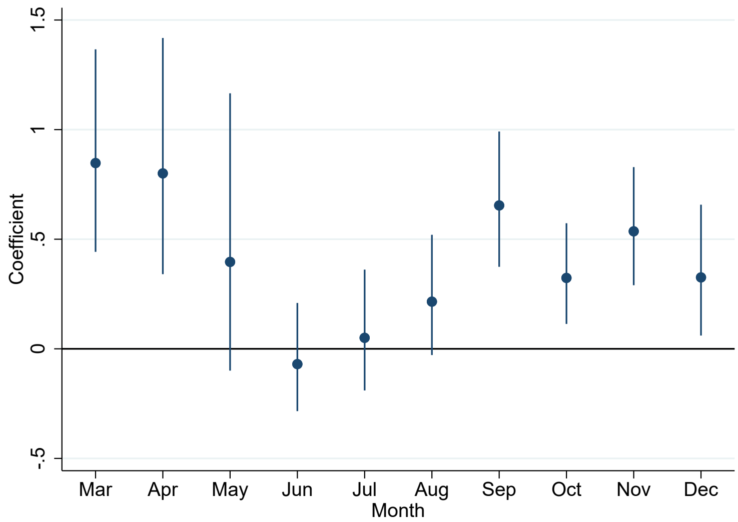
Table 16: Robustness: separate week specific dummies(w8, w9 and w10). Classification of Mecklenburg-Vorpommern changed (see appendix 5.2)

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break W8	0.181	-0.0890	-0.447^{b}	-0.340^{b}	-0.284^{c}	0.000662	-0.0341	0.136	0.152	0.132
	(0.120)	(0.166)	(0.176)	(0.153)	(0.149)	(0.122)	(0.0972)	(0.113)	(0.129)	(0.148)
Break W9	0.614^{a}	0.588^{a}	0.334	-0.0723	0.0490	0.195^{c}	0.503^{a}	0.280^{a}	0.429^{a}	0.282^{b}
	(0.125)	(0.149)	(0.221)	(0.132)	(0.131)	(0.113)	(0.0936)	(0.0871)	(0.0881)	(0.113)
Break W10	0.416^{b}	0.563^{b}	-0.154	-0.114	-0.147	0.135	0.0365	-0.107	0.317^{b}	-0.131
	(0.174)	(0.215)	(0.305)	(0.275)	(0.205)	(0.197)	(0.182)	(0.110)	(0.159)	(0.169)
Population	0.577^{a}	1.100^{a}	1.115^{a}	0.859^{a}	1.014^{a}	0.760^{a}	1.143^{a}	1.239^{a}	1.273^{a}	1.222^{a}
	(0.132)	(0.174)	(0.190)	(0.235)	(0.221)	(0.135)	(0.118)	(0.0984)	(0.106)	(0.116)
Median age	5.135^{a}	9.172^{a}	8.629^{a}	6.222^{b}	4.618^{b}	4.012^{a}	-0.303	-0.657	2.059	2.195
	(1.394)	(1.582)	(1.753)	(2.477)	(2.247)	(1.412)	(1.545)	(1.304)	(1.253)	(1.383)
Share below 14	0.0590	0.234	0.625	1.250^{c}	1.562^{b}	0.911^{c}	1.402^{a}	0.827^{c}	0.524	-0.0560
	(0.509)	(0.619)	(0.827)	(0.655)	(0.636)	(0.485)	(0.492)	(0.455)	(0.439)	(0.459)
Share over age 60	-4.054^{a}	-5.575^{a}	-4.445^{a}	-2.987^{c}	-2.842^{c}	-3.572^{a}	-0.686	-0.463	-1.156	-0.394
	(0.857)	(0.975)	(1.126)	(1.518)	(1.476)	(0.894)	(0.942)	(0.881)	(0.930)	(1.077)
Area (km sq.)	0.00253	-0.217^{a}	-0.264^{a}	-0.304^{a}	-0.243^{a}	-0.187^{a}	-0.229^{a}	-0.0769^{b}	-0.124^{a}	-0.123^{a}
	(0.0440)	(0.0451)	(0.0590)	(0.0758)	(0.0703)	(0.0418)	(0.0398)	(0.0353)	(0.0299)	(0.0328)
Income	0.479^{a}	0.202^{c}	0.162	0.374^{b}	0.235	0.424^{a}	0.145	-0.0781	-0.120	-0.0460
	(0.0989)	(0.116)	(0.141)	(0.182)	(0.162)	(0.106)	(0.101)	(0.0837)	(0.0765)	(0.0852)
Interm. urb.	-0.00375	0.0976	-0.0610	-0.144	-0.281^{b}	-0.195^{b}	-0.0804	-0.228^{a}	-0.147^{b}	-0.0495
	(0.0865)	(0.0953)	(0.125)	(0.146)	(0.136)	(0.0810)	(0.0710)	(0.0693)	(0.0563)	(0.0655)
Rural	-0.0404	0.324^{b}	0.0502	-0.0222	-0.182	-0.174	0.00185	-0.146	-0.0853	0.0247
	(0.104)	(0.151)	(0.191)	(0.197)	(0.165)	(0.120)	(0.108)	(0.103)	(0.0868)	(0.0935)
BE	-0.128	1.407^{a}	1.803^{a}	0.644^{c}	0.160	0.0327	-0.625^{a}	0.609^{a}	-1.447^{a}	-0.830^{a}
	(0.243)	(0.255)	(0.394)	(0.355)	(0.285)	(0.204)	(0.204)	(0.217)	(0.178)	(0.184)
DE	-0.123	0.682^{a}	0.920^{a}	-0.104	-0.722^{a}	-0.220^{b}	-1.248^{a}	-1.067^{a}	-1.460^{a}	-0.444^{a}
	(0.179)	(0.181)	(0.236)	(0.206)	(0.191)	(0.104)	(0.138)	(0.105)	(0.126)	(0.128)
DK	-0.346	0.974^{a}	1.496^{a}	0.389	-0.453	-0.258	-0.220	-1.159^{a}	-1.431^{a}	0.267
	(0.220)	(0.277)	(0.371)	(0.412)	(0.338)	(0.335)	(0.188)	(0.147)	(0.169)	(0.182)
EE	2.947^{a}	5.205^{a}	6.918^{a}	6.683^{a}	4.362^{a}	4.915^{a}	3.594^{a}	1.611^{a}	1.233^{a}	2.448^{a}
	(0.259)	(0.280)	(0.371)	(0.393)	(0.356)	(0.232)	(0.252)	(0.193)	(0.190)	(0.216)
FI	-1.403^{a}	0.113	1.125^{b}	-0.415	-1.440^{a}	-1.177^{a}	-1.697^{a}	-2.495^{a}	-3.078^{a}	-2.156^{a}
	(0.286)	(0.316)	(0.480)	(0.444)	(0.389)	(0.210)	(0.302)	(0.203)	(0.264)	(0.300)
IE	-0.869^{a}	2.268^{a}	2.919^{a}	0.333	-0.935^{a}	-0.542^{c}	-0.789^{a}	-1.196^{a}	-2.665^{a}	-0.942^{a}
	(0.283)	(0.357)	(0.523)	(0.416)	(0.351)	(0.275)	(0.266)	(0.255)	(0.235)	(0.250)
LV	-1.502^{a}	-0.260	1.046^{a}	-0.0111	-1.248^{a}	-0.750^{a}	-2.169^{a}	-1.447^{a}	-1.380^{a}	0.268
	(0.205)	(0.220)	(0.319)	(0.339)	(0.314)	(0.193)	(0.213)	(0.165)	(0.176)	(0.185)
NL	-1.059^{a}	1.414^{a}	1.258^{a}	0.205	-1.002^{a}	-0.140	-0.387^{c}	-0.153	-1.427^{a}	0.346^{c}
	(0.231)	(0.243)	(0.347)	(0.343)	(0.302)	(0.194)	(0.206)	(0.147)	(0.165)	(0.183)
NO	-1.570^{a}	0.220	0.981^{b}	-0.00273	-1.393^{a}	-0.809^{a}	-1.586^{a}	-2.285^{a}	-2.382^{a}	-1.623^{a}
	(0.283)	(0.280)	(0.446)	(0.381)	(0.373)	(0.253)	(0.236)	(0.206)	(0.254)	(0.361)
PT	-1.316^{a}	0.708^{c}	1.717^{a}	1.730^{a}	0.656	0.339	-0.527	-1.733^{a}	-3.327^{a}	-2.114^{a}
	(0.462)	(0.383)	(0.381)	(0.474)	(0.415)	(0.273)	(0.336)	(0.330)	(0.303)	(0.263)
SE	-0.677^{b}	2.432^{a}	4.565^{a}	4.245^{a}	1.541^{a}	0.836^{a}	-0.600^{b}	-0.985^{a}	-0.463^{c}	0.780^{a}
	(0.339)	(0.375)	(0.421)	(0.458)	(0.433)	(0.299)	(0.268)	(0.230)	(0.254)	(0.279)
SI	-0.984^{a}	-0.674^{a}	-0.571^{c}	1.063^{a}	0.293	0.247	-0.272	0.312^{b}	-0.316^{b}	0.715^{a}
	(0.216)	(0.221)	(0.329)	(0.370)	(0.253)	(0.183)	(0.178)	(0.135)	(0.142)	(0.186)
SK	-2.497^{a}	-0.800^{b}	-0.583	-0.0218	-0.526	-0.307	-0.459	-0.306^{c}	-1.339^{a}	0.353^{c}
	(0.281)	(0.341)	(0.442)	(0.447)	(0.326)	(0.320)	(0.283)	(0.177)	(0.213)	(0.194)
Constant	-12.28^{a}	-27.24^{a}	-30.89^{a}	-25.89^{a}	-21.10^{a}	-13.26^{a}	-8.420^{b}	-4.530	-10.70^{a}	-13.17^{a}
	(3.157)	(3.779)	(4.611)	(4.788)	(4.830)	(2.916)	(3.577)	(2.791)	(2.510)	(2.146)
Observations	647	649	649	649	649	649	649	649	649	649

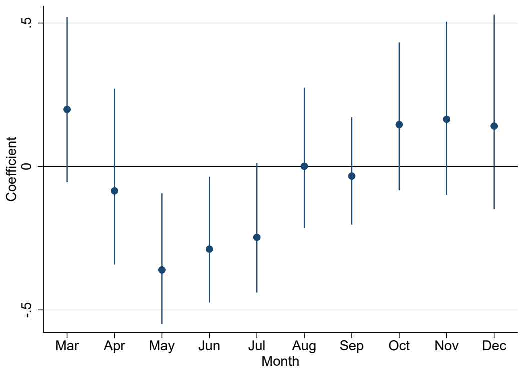
Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$



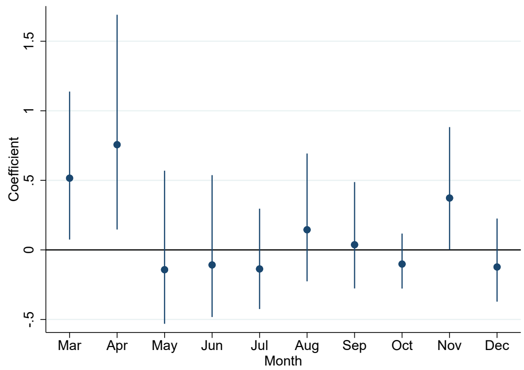
(a) Cases: Joint dummy (8, 9 or 10)



(b) Cases: Week 9 dummy



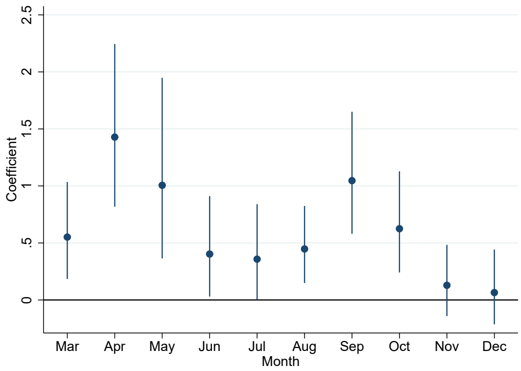
(c) Cases: Week 8 dummy



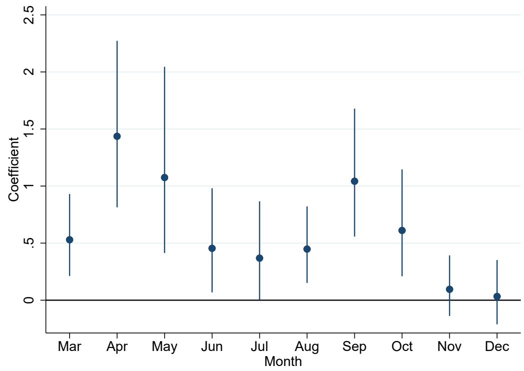
(d) Cases: Week 10 dummy

Figure 8: Robustness after changing classification in one German state: Coefficient plot of the joint dummy per month in graph 8a. Sub-graphs 8c,8b 8d show week 8, 9 and 10 dummies (in a single regression without the joint dummy).

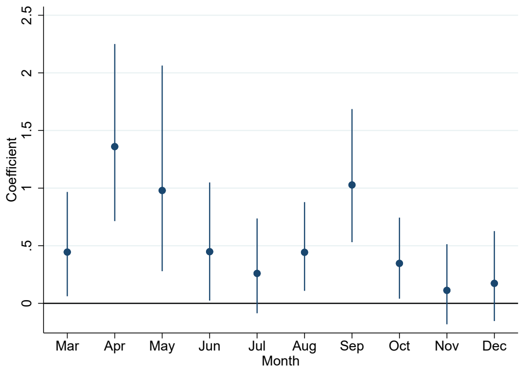
Note: As discussed in the data appendix 5.2 there is some uncertainty is on how to classify the school-break in Mecklenburg-Vorpommern. NUTS 3 regions in these states have been dropped for this robustness check. See tables 16 and 15 for the full results.



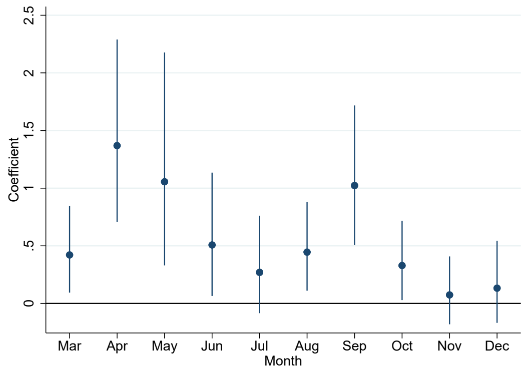
(a) Cases: Week 9 dummy (without distance)



(b) Cases: Week 9 dummy (with distance)



(c) Cases: Week 9 dummy (without distance)



(d) Cases: Week 9 dummy (with distance)

Figure 9: Gravity robustness without country fixed effect. Comparison with/without distance to Ischgl. Coefficient plot of the week 9 dummy only from a regression as in equation 2. Lower panel (c,d) excludes Belgium.

Note: Here we add distance to Ischgl as a control variable but remove the country fixed effect to investigate the role of absolute distance on the results. Results are very similar if Belgium is removed from the sample(lower panel). See discussion in 5.2. Full results available on request.

Table 17: Gravity robustness results using a joint late dummy. Distance from NUTS 3 region to Ischgl added.

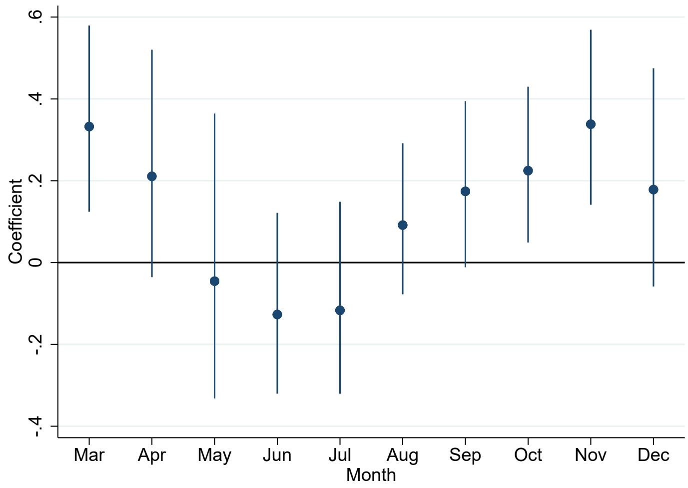
	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break =>W8	0.287^a	0.191^c	-0.0465	-0.136	-0.124	0.0876	0.160^c	0.203^b	0.291^a	0.164
	(0.0858)	(0.115)	(0.180)	(0.126)	(0.132)	(0.0849)	(0.0868)	(0.0781)	(0.0803)	(0.113)
Distance	-0.478^a	-0.528^a	-0.261^c	0.0638	-0.0553	-0.202^b	-0.351^a	-0.150^b	-0.218^b	-0.304^a
	(0.0857)	(0.0946)	(0.155)	(0.109)	(0.0817)	(0.0856)	(0.0817)	(0.0600)	(0.0909)	(0.101)
Population	0.695^a	1.214^a	1.050^a	0.725^a	0.936^a	0.823^a	1.204^a	1.308^a	1.336^a	1.383^a
	(0.134)	(0.159)	(0.199)	(0.235)	(0.220)	(0.136)	(0.106)	(0.0873)	(0.102)	(0.122)
Median age	5.733^a	9.768^a	10.37^a	7.773^a	5.860^b	4.494^a	0.933	0.107	2.665^b	2.481^c
	(1.232)	(1.356)	(1.568)	(2.362)	(2.321)	(1.358)	(1.404)	(1.167)	(1.069)	(1.359)
Share below 14	-0.421	-0.393	0.0515	1.049	1.298^c	0.702	0.917^b	0.693^c	0.256	-0.258
	(0.465)	(0.624)	(0.872)	(0.657)	(0.659)	(0.450)	(0.444)	(0.416)	(0.429)	(0.471)
Share over age 60	-4.441^a	-6.071^a	-5.855^a	-4.379^a	-3.939^b	-3.979^a	-1.647^b	-1.035	-1.626^b	-0.401
	(0.675)	(0.805)	(1.083)	(1.435)	(1.556)	(0.851)	(0.792)	(0.726)	(0.787)	(1.078)
Area (km sq.)	0.000652	-0.208^a	-0.255^a	-0.283^a	-0.233^a	-0.187^a	-0.237^a	-0.0907^b	-0.124^a	-0.150^a
	(0.0421)	(0.0475)	(0.0625)	(0.0751)	(0.0679)	(0.0425)	(0.0405)	(0.0349)	(0.0316)	(0.0331)
Income	0.382^a	0.111	0.197	0.435^b	0.268	0.363^a	0.0870	-0.143^c	-0.176^b	-0.159^c
	(0.0986)	(0.110)	(0.155)	(0.183)	(0.163)	(0.103)	(0.0894)	(0.0740)	(0.0698)	(0.0883)
Interm. urb.	-0.0245	0.0677	-0.0811	-0.188	-0.296^b	-0.212^a	-0.0828	-0.222^a	-0.165^a	-0.0537
	(0.0765)	(0.0915)	(0.135)	(0.141)	(0.144)	(0.0781)	(0.0674)	(0.0706)	(0.0528)	(0.0595)
Rural	-0.0668	0.301^c	0.0204	-0.118	-0.226	-0.211^c	-0.00945	-0.165	-0.112	0.0225
	(0.100)	(0.152)	(0.210)	(0.184)	(0.171)	(0.116)	(0.102)	(0.101)	(0.0831)	(0.0865)
BE	0.798^a	2.549^a	2.738^a	0.797^b	0.527^c	0.403^b	0.236	0.871^a	-0.994^a	-0.398^c
	(0.216)	(0.261)	(0.410)	(0.371)	(0.289)	(0.186)	(0.221)	(0.217)	(0.194)	(0.202)
DE	0.188	1.081^a	1.236^a	-0.0343	-0.595^a	-0.0844	-0.963^a	-0.975^a	-1.295^a	-0.318^a
	(0.135)	(0.195)	(0.299)	(0.195)	(0.179)	(0.0981)	(0.167)	(0.0883)	(0.0981)	(0.102)
DK	0.471^b	1.915^a	2.131^a	0.467	-0.217	0.106	0.469^b	-0.875^a	-1.022^a	0.732^a
	(0.234)	(0.323)	(0.458)	(0.434)	(0.345)	(0.345)	(0.221)	(0.153)	(0.203)	(0.210)
EE	4.243^a	6.738^a	8.152^a	6.859^a	4.839^a	5.440^a	4.779^a	2.018^a	1.856^a	3.116^a
	(0.252)	(0.310)	(0.472)	(0.449)	(0.369)	(0.245)	(0.289)	(0.225)	(0.257)	(0.277)
FI	-0.0616	1.693^a	2.152^a	-0.286	-1.040^b	-0.589^b	-0.578^c	-2.092^a	-2.423^a	-1.466^a
	(0.307)	(0.339)	(0.538)	(0.520)	(0.424)	(0.267)	(0.332)	(0.224)	(0.313)	(0.370)
IE	0.115	3.237^a	3.266^a	0.0563	-0.912^b	-0.185	-0.141	-0.944^a	-2.291^a	-0.294
	(0.309)	(0.391)	(0.683)	(0.531)	(0.386)	(0.295)	(0.342)	(0.297)	(0.306)	(0.325)
LV	-0.648^a	0.754^b	1.829^a	0.0968	-0.970^a	-0.394^c	-1.427^a	-1.179^a	-0.959^a	0.730^a
	(0.217)	(0.297)	(0.459)	(0.381)	(0.317)	(0.210)	(0.256)	(0.195)	(0.223)	(0.218)
NL	-0.306	2.219^a	1.796^a	0.219	-0.799^b	0.136	0.209	0.0417	-1.113^a	0.698^a
	(0.236)	(0.269)	(0.428)	(0.389)	(0.331)	(0.206)	(0.220)	(0.158)	(0.184)	(0.198)
NO	-0.469	1.390^a	1.516^b	-0.173	-1.268^a	-0.364	-0.782^a	-1.962^a	-1.905^a	-0.931^b
	(0.307)	(0.316)	(0.590)	(0.483)	(0.409)	(0.310)	(0.291)	(0.249)	(0.306)	(0.402)
PT	0.124	2.315^a	3.037^a	2.180^a	1.298^a	1.021^a	0.798^a	-1.135^a	-2.570^a	-1.405^a
	(0.401)	(0.375)	(0.452)	(0.479)	(0.420)	(0.257)	(0.299)	(0.266)	(0.279)	(0.278)
SE	0.425	3.686^a	5.357^a	4.322^a	1.849^a	1.313^a	0.310	-0.642^a	0.0641	1.377^a
	(0.342)	(0.396)	(0.513)	(0.540)	(0.459)	(0.327)	(0.303)	(0.237)	(0.296)	(0.326)
SI	-0.477^c	-0.0712	-0.0389	1.172^a	0.523^c	0.437^b	0.206	0.444^a	-0.0864	0.924^a
	(0.271)	(0.343)	(0.345)	(0.323)	(0.286)	(0.206)	(0.270)	(0.134)	(0.175)	(0.211)
SK	-1.946^a	-0.135	-0.162	0.0108	-0.367	-0.120	-0.0557	-0.267	-1.123^a	0.528^a
	(0.243)	(0.323)	(0.451)	(0.471)	(0.313)	(0.280)	(0.266)	(0.189)	(0.199)	(0.194)
Constant	-9.869^a	-23.94^a	-29.62^a	-26.15^a	-20.68^a	-12.30^a	-6.925^c	-4.541^c	-9.814^a	-12.72^a
	(3.089)	(3.860)	(4.767)	(4.626)	(4.889)	(2.915)	(3.499)	(2.718)	(2.501)	(2.239)
Observations	645	647	647	647	647	647	647	647	647	647

Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$

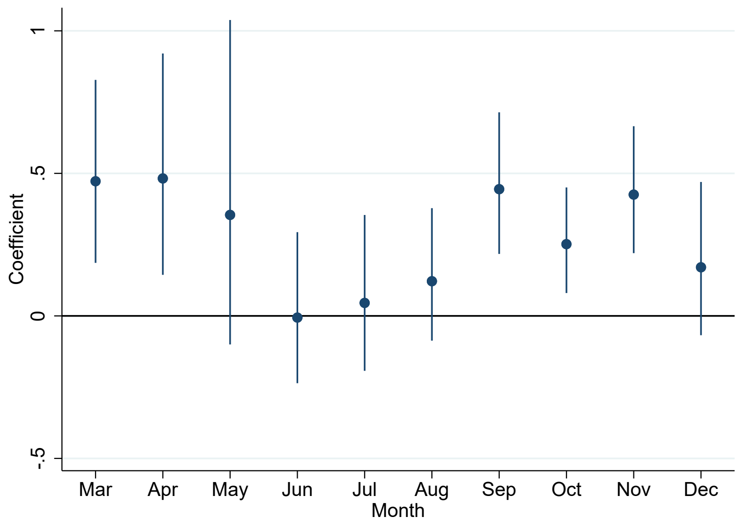
Table 18: Gravity robustness results using a joint late dummy. Separate week specific dummies(w8, w9 and w10)

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Break W8	0.191^b	-0.00574	-0.340^b	-0.248^c	-0.265^c	0.0584	-0.0108	0.197^c	0.232^b	0.181
	(0.0846)	(0.106)	(0.155)	(0.145)	(0.156)	(0.0968)	(0.0792)	(0.1000)	(0.0939)	(0.130)
Break W9	0.387^a	0.394^a	0.303	-0.00585	0.0445	0.115	0.368^a	0.225^a	0.355^a	0.158
	(0.109)	(0.131)	(0.206)	(0.133)	(0.130)	(0.104)	(0.0863)	(0.0744)	(0.0785)	(0.115)
Break W10	0.493^a	0.708^a	-0.0510	-0.0709	-0.131	0.208	0.105	-0.0488	0.402^a	-0.0447
	(0.134)	(0.178)	(0.310)	(0.268)	(0.204)	(0.179)	(0.163)	(0.105)	(0.145)	(0.172)
Distance	-0.450^a	-0.479^a	-0.145	0.104	0.000724	-0.197^b	-0.280^a	-0.134^b	-0.201^b	-0.299^a
	(0.0857)	(0.0966)	(0.145)	(0.115)	(0.0684)	(0.0913)	(0.0690)	(0.0635)	(0.0962)	(0.106)
Population	0.716^a	1.314^a	1.147^a	0.767^a	0.982^a	0.841^a	1.257^a	1.293^a	1.363^a	1.363^a
	(0.136)	(0.153)	(0.198)	(0.239)	(0.224)	(0.135)	(0.105)	(0.0897)	(0.100)	(0.116)
Median age	5.587^a	9.446^a	9.314^a	7.418^a	5.349^b	4.478^a	0.278	-0.0990	2.536^b	2.385^c
	(1.278)	(1.400)	(1.620)	(2.397)	(2.294)	(1.378)	(1.412)	(1.216)	(1.098)	(1.360)
Share below 14	-0.271	-0.100	0.484	1.215^c	1.506^b	0.746^c	1.169^a	0.700^c	0.343	-0.283
	(0.456)	(0.579)	(0.798)	(0.654)	(0.633)	(0.444)	(0.435)	(0.418)	(0.426)	(0.468)
Share over age 60	-4.221^a	-5.610^a	-4.968^a	-4.057^a	-3.511^b	-3.922^a	-1.116	-0.954	-1.476^c	-0.397
	(0.715)	(0.838)	(1.094)	(1.436)	(1.514)	(0.841)	(0.790)	(0.744)	(0.800)	(1.064)
Area (km sq.)	-0.00976	-0.241^a	-0.265^a	-0.291^a	-0.238^a	-0.194^a	-0.240^a	-0.0784^b	-0.131^a	-0.139^a
	(0.0426)	(0.0429)	(0.0637)	(0.0780)	(0.0709)	(0.0429)	(0.0396)	(0.0377)	(0.0317)	(0.0344)
Income	0.367^a	0.0414	0.117	0.403^b	0.230	0.351^a	0.0418	-0.137^c	-0.196^a	-0.149^c
	(0.100)	(0.105)	(0.148)	(0.185)	(0.166)	(0.103)	(0.0862)	(0.0744)	(0.0687)	(0.0855)
Interm. urb.	-0.0225	0.0813	-0.0965	-0.190	-0.303^b	-0.208^a	-0.0943	-0.234^a	-0.163^a	-0.0625
	(0.0757)	(0.0876)	(0.127)	(0.141)	(0.138)	(0.0784)	(0.0669)	(0.0716)	(0.0519)	(0.0590)
Rural	-0.0777	0.296^b	-0.0293	-0.133	-0.250	-0.210^c	-0.0413	-0.179^c	-0.116	0.0140
	(0.0960)	(0.149)	(0.207)	(0.189)	(0.162)	(0.116)	(0.102)	(0.103)	(0.0823)	(0.0883)
BE	0.591^b	2.120^a	2.028^a	0.531	0.185	0.343	-0.183	0.835^a	-1.126^a	-0.378^c
	(0.236)	(0.268)	(0.419)	(0.402)	(0.288)	(0.220)	(0.229)	(0.233)	(0.217)	(0.214)
DE	0.108	0.910^a	0.995^a	-0.128	-0.710^a	-0.111	-1.103^a	-0.974^a	-1.346^a	-0.301^a
	(0.132)	(0.183)	(0.263)	(0.196)	(0.191)	(0.103)	(0.151)	(0.0949)	(0.105)	(0.104)
DK	0.371	1.721^a	1.774^a	0.336	-0.390	0.0816	0.256	-0.904^a	-1.084^a	0.733^a
	(0.225)	(0.302)	(0.424)	(0.446)	(0.356)	(0.352)	(0.216)	(0.164)	(0.213)	(0.220)
EE	4.021^a	6.274^a	7.282^a	6.541^a	4.420^a	5.381^a	4.259^a	1.945^a	1.707^a	3.116^a
	(0.287)	(0.329)	(0.470)	(0.496)	(0.359)	(0.290)	(0.300)	(0.259)	(0.297)	(0.294)
FI	-0.274	1.272^a	1.529^a	-0.525	-1.340^a	-0.652^b	-0.941^a	-2.101^a	-2.549^a	-1.430^a
	(0.310)	(0.341)	(0.544)	(0.529)	(0.403)	(0.280)	(0.337)	(0.229)	(0.335)	(0.370)
IE	0.109	3.240^a	3.144^a	0.0205	-0.972^b	-0.178	-0.220	-0.987^a	-2.297^a	-0.321
	(0.299)	(0.365)	(0.642)	(0.540)	(0.392)	(0.304)	(0.313)	(0.297)	(0.310)	(0.331)
LV	-0.768^a	0.484^c	1.326^a	-0.0877	-1.213^a	-0.428^c	-1.728^a	-1.221^a	-1.046^a	0.731^a
	(0.223)	(0.288)	(0.415)	(0.409)	(0.311)	(0.226)	(0.251)	(0.219)	(0.250)	(0.226)
NL	-0.410^c	1.988^a	1.410^a	0.0749	-0.985^a	0.104	-0.0190	0.0211	-1.185^a	0.708^a
	(0.222)	(0.248)	(0.384)	(0.385)	(0.306)	(0.216)	(0.216)	(0.158)	(0.189)	(0.199)
NO	-0.537^c	1.289^a	1.269^b	-0.260	-1.387^a	-0.373	-0.932^a	-1.997^a	-1.941^a	-0.943^b
	(0.299)	(0.297)	(0.564)	(0.496)	(0.412)	(0.318)	(0.273)	(0.253)	(0.318)	(0.404)
PT	-0.0835	1.878^a	2.259^a	1.892^a	0.923^b	0.963^a	0.335	-1.190^a	-2.708^a	-1.396^a
	(0.424)	(0.396)	(0.438)	(0.508)	(0.426)	(0.293)	(0.304)	(0.291)	(0.312)	(0.293)
SE	0.277	3.401^a	4.894^a	4.148^a	1.626^a	1.273^a	0.0371	-0.663^a	-0.0233	1.393^a
	(0.357)	(0.396)	(0.486)	(0.545)	(0.440)	(0.332)	(0.288)	(0.249)	(0.309)	(0.331)
SI	-0.588^b	-0.322	-0.457	1.016^a	0.321	0.402^c	-0.0405	0.422^a	-0.164	0.936^a
	(0.235)	(0.261)	(0.332)	(0.375)	(0.254)	(0.206)	(0.200)	(0.139)	(0.165)	(0.217)
SK	-2.067^a	-0.441	-0.494	-0.127	-0.526	-0.172	-0.241	-0.233	-1.208^a	0.580^a
	(0.250)	(0.324)	(0.465)	(0.464)	(0.331)	(0.297)	(0.278)	(0.189)	(0.214)	(0.188)
Constant	-10.60^a	-25.55^a	-30.55^a	-26.63^a	-21.13^a	-12.62^a	-7.372^b	-4.084	-10.21^a	-12.28^a
	(3.036)	(3.597)	(4.479)	(4.735)	(4.952)	(2.951)	(3.491)	(2.770)	(2.452)	(2.236)
Observations	645	647	647	647	647	647	647	647	647	647

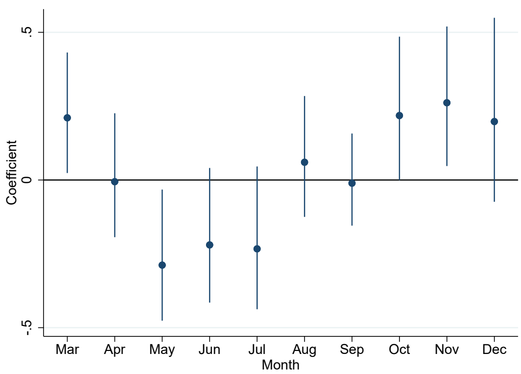
Standard errors, clustered at NUTS 2 level, in parenthesis. ^{c} $p < .1$, ^{b} $p < .05$, ^{a} $p < .01$



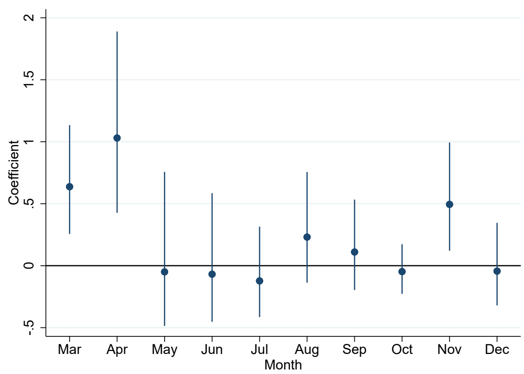
(a) Cases: Joint dummy (8, 9 or 10)



(b) Cases: Week 9 dummy



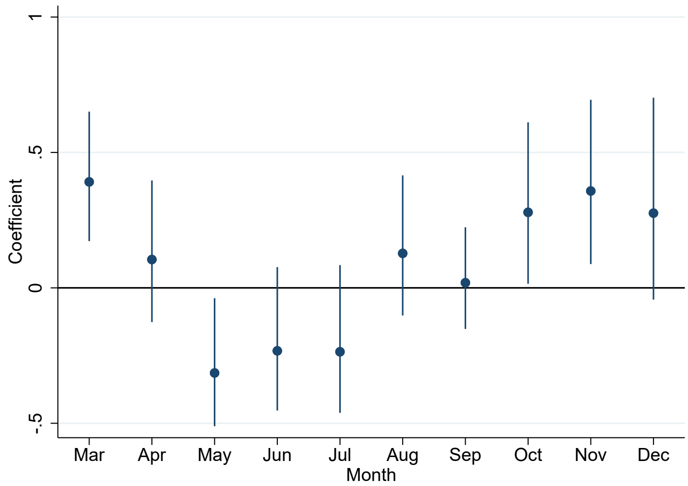
(c) Cases: Week 8 dummy



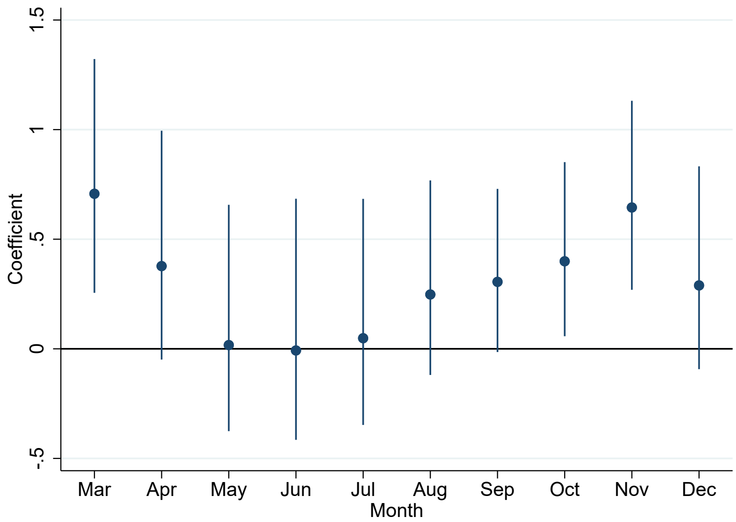
(d) Cases: Week 10 dummy

Figure 10: Gravity robustness: Coefficient plot of the joint dummy per month in graph 10a. Sub-graphs 10c,10b 10d show week 8, 9 and 10 dummies (in a single regression without the joint dummy).

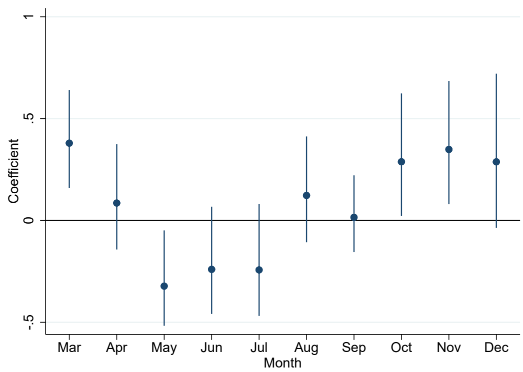
Note: Here we add distance to Ischgl as a control variable. See tables 17 and 18 for the full results and appendix 5.2 for a discussion.



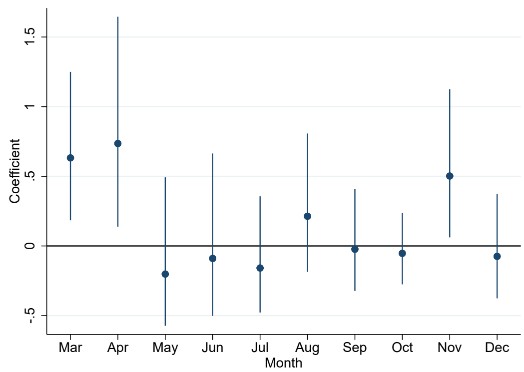
(a) Cases: Joint dummy (8, 9 or 10)



(b) Cases: Week 9 dummy



(c) Cases: Week 8 dummy



(d) Cases: Week 10 dummy

Figure 11: Gravity robustness: Dropping the two regions in Germany close to the Austrian Alps. Coefficient plot of the joint dummy per month in graph 11a. Sub-graphs 11c,11b 11d show week 8, 9 and 10 dummies (in a single regression without the joint dummy).

Note: See discussion in appendix 5.2. Full results available on request.