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Abstract: This paper investigates the dynamics of behavioral changes during a crisis. We study this in the context of the first year of the Covid-19 pandemic, where behavioral responses were important in mitigating the costs of the pandemic. To identify behavioral responses to unanticipated and transient health risk shocks, we combine high-frequency cellphone mobility data with detailed incidence data in Germany. Using an event-study design on local outbreaks, we find that county-level mobility immediately and significantly decreased by about 2.5% in response to an outbreak independent of non-pharmaceutical interventions. We also find that the reproduction rate decreased by about 17% in response to a local outbreak. Both behavioral responses are quite persistent even after the relative health risk has dissipated. By the time of the second wave, the behavioral response to a second or third shock is small or negligible. Our results demonstrate the importance of (1) integrating behavioral persistence in models used to study behavior and policies that change behavior, (2) the effectiveness of policies that provide high-frequency localized information on health risks, and (3) the potential persistence of behavioral changes after the Covid-19 pandemic has passed.

JEL: D90, H12, I12, I18
Keywords: Dynamics, Behavioral Response, Crisis, Covid-19

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1 Introduction

In times of crisis, individuals make drastic changes in their behavior either in direct response to a hardship or to mitigate the increased risk. Research has shown that behavioral changes can persistent long after the risk or crisis has passed. For example, current research using retrospective data shows that previous exposure to an early life financial crisis (Malmendier and Nagel, 2011; Osili and Paulson, 2014), violent conflict (Callen et al., 2014; Kesternich et al., 2015), or natural disaster (Cameron and Shah, 2015) affects behavior many years or decades after the event. While the literature has provided important evidence on the possible channels for the changes in behavior, little is known about the *dynamics* of the behavioral changes during a crisis (Rasul, 2020). In other words, how does behavior change at the time of a major shock? Are there lags in adjustment? How does the history of exposure to shocks affect future behavioral responses?

Credible estimation of behavioral dynamics outside of the lab is challenging as it requires high frequency data taken at the time of an unanticipated and arguably random or exogenous shock. Furthermore, in order to understand the persistence of the behavioral changes, the shock must be transient. Lastly, to understand how the history of exposure to shocks affects future behavior, the setting must include multiple exposures to shocks over time.

In this paper, we study the behavioral responses in a recent global health crisis, the Covid-19 pandemic, using high-frequency panel data on infections and cell-phone mobility data in Germany. In particular, we estimate the dynamic effects of unanticipated, local, and transient outbreaks on mobility and the reproduction rate. Our empirical strategy is based on Covid-19[1] being an *overdispersed* pathogen, where a small fraction of individuals are responsible for a large fraction of the transmission. In the case of Covid-19, studies have shown that only 10–20% of individuals are responsible for 80–90% of transmission in clusters often called "super-spreader" events (see e.g. Baggett et al., 2020; Endo et al., 2020; Hamner et al., 2020; James et al., 2020; Lemieux et al., 2020; Majra et al., 2021;

[1]The expressions Covid-19, coronavirus and SARS-CoV-2 are used interchangeably.

Riou and Althaus, 2020).[2] This feature of the virus implies that the local risk level can change unexpectedly and dramatically when an outbreak occurs. We also find that the increased relative risk due to outbreaks is transient, where the incidence rate converges to that of neighboring counties after two to three weeks. In summary, our strategy allows us to investigate behavioral changes both at the time of the shock and the behavioral dynamics after a transient shock has dissipated.

We estimate the effect of a shock using an event-study approach that examines the changes in behavior in a county when an unanticipated and transient outbreak occurs.[3] We identify local unanticipated outbreaks by comparing the number of cases in a seven-day period to the number of cases we would expect based on a parsimonious epidemiological model. We define a local unexpected outbreak as a county and a seven-day period where the observed number of cases exceeds the expected number based on our model. Our preferred specification identifies 259 outbreaks between February and November of 2020.[4]

We find that a local outbreak significantly reduces the number of trips taken inside the county and also reduces the number of trips between other counties and the outbreak county. The number of trips is reduced by about 2.5%. We do not, however, find any changes in the number of trips before the outbreak is publicly reported by the national health agency, making it unlikely that the changes are due to knowledge of a risky event or of individuals with symptoms. The mobility data measures only one aspect of many behavioral adjustments that can reduce risk. To capture the overall impact of behavioral changes on disease transmission, we study changes in the reproduction rate which is defined as the expected number of cases directly generated by one case in a population. We find a substantial decrease in the reproduction rate after an outbreak of about 17%.

[2] Some commonly known "super-spreader" events or clusters are the example of a Korean woman infecting 1000+ others in a few days and a wedding in Hamm, Germany, that triggered a surge in infections in the beginning of September.

[3] We examine mobility measured using cell-phone data on the number of trips taken within and across counties each day and the reproduction rate. See Section 3 for more information.

[4] Our preferred specification requires that the excess cases in a county is at the 98^{th} percentile for all counties in Germany between February and November 2020. This definition captures the well-known outbreaks (*e.g.* Heinsberg in February, Gütersloh in June, Hamm in September, and Berchtesgaden in October). See Section 4.2 for more information.

Controlling for non-pharmaceutical interventions (NPIs) makes little difference in our estimates which indicates that we are capturing a voluntary response. Likewise, we provide evidence that the behavioral responses are not concentrated at commuting hours and, hence, are unlikely to be driven by work-from-home policies at firms.

The dynamics of the behavioral response has several noteworthy features. First, the changes in mobility and reproduction rate are quite persistent. The changes in mobility are essentially unchanged more than a month after an outbreak by which time the increased relative risk has dissipated. Likewise, more than a month after the outbreak, the reproduction rate is still reduced by 11%, about sixty percent of the short-run effect. The behavioral response also depends on the history of outbreaks (*e.g.* first, second, third outbreak) in a county and the point in the pandemic at which the outbreak occurred. The mobility response to the first outbreak in a county was 1.5 to 2.2 times stronger in the second wave compared to the first wave.[5] Conversely, counties that had a subsequent outbreak in the second wave had *no* measured mobility response. The dynamics of the behavioral response for the reproduction rate are similar to the results for mobility, where the response was stronger in the second wave compared to the first wave. In contrast, the response to a subsequent outbreak in the second wave is significant but 62% of the response to a first outbreak around the same time. These results are suggestive of important fixed costs in making behavioral changes. The results on the reproduction rate suggest that some forms of behavioral response (*e.g.* wearing a mask) have important marginal costs and depend less on the history of shocks.

We further investigate heterogeneity in response to local outbreaks along three distinct dimensions: Counties may differ in (i) costs of adjusting mobility, *e.g.* depending on the fraction of workers that can work from home, (ii) relative risks of infection, *e.g.* depending on transportation modes and structure of urbanization, and (iii) average beliefs about the risk of the virus. We find that counties with a larger touristic sector and a larger share of workers that can work from home reduce their mobility more in response to local

[5]Interpreting differences in behavioral responses at different points in time is challenging as the environment was also changing (*e.g.* the severity of NPIs). The behavioral response may be greater during the second wave due to behavioral reasons, or because the presence of fewer NPIs allowed for a stronger voluntary response.

outbreaks indicating that behavioral responses are indeed larger if costs are lower.[6] We do not, however, find evidence that prevalence of public transport or beliefs on the risk of Covid-19 affect the mobility responses.[7] We do not find evidence that the reproduction-rate response varies by costs of adjusting mobility or the other proxies. Finally, we provide evidence that our results are robust to estimators that account for heterogeneous effects, and to varying the definition of outbreaks. We also find no measured effect when using placebo outbreaks.

This paper contributes to several strands of literature. First, the paper adds to a growing literature in economics studying the role of information in shaping people's health behavior and beliefs (e.g. Bollinger et al., 2011; Cawley et al., 2021; Dupas, 2011; Oster, 2018b; Wisdom et al., 2010). This body of literature investigates whether people adjust their behavior to information on health risk. Yet, evidence on that matter is inconclusive. One strand of literature shows that people appear reluctant to undertake costly behaviors with health benefits. For example, people are resistant to changing sexual behavior in the face of HIV, to change diet in response to a diabetes diagnosis, and do not get regular cancer screenings (Caldwell et al., 1999; Cummings and Cooper, 2011; Hut and Oster, 2018; Kim et al., 2019; Oster, 2012, 2018a; Prina and Royer, 2014). Another strand of literature, however, argues that people are sensitive to changes in health risk and demand for self-protection (Chan, 2015; Kremer, 1996; Lautharte and Rasul, 2022; Oster, 2018b; Philipson, 2008). These studies document a prevalence-elasticity of private demand for prevention against disease. Lautharte and Rasul (2022), for example, show that people respond to public health alerts linking the Zika virus to the risk of congenital disease for those *in utero*. We add to this body of literature by investigating whether and how individuals adjust their behavior to high-frequency localized information about transitory shocks to the level of health risk. Studying unanticipated outbreaks allows us to report

[6] We take the share of people with a college-degree as measure for the likelihood of working from home. Previous literature shows that people with higher educational degree are more likely to do home office in response to the pandemic (von Gaudecker et al., 2020).

[7] We use the vote share of the AfD, a right-wing party, in the last state elections as a proxy for beliefs. A number of studies in the US have shown that partisanship affects people's beliefs on the risks of Covid-19. Similarly in Germany, the AfD party was critical of the government handling of Covid-19 and one may expect that counties with high AfD vote shares would, likewise, respond less to an outbreak.

credible estimates of how behavior changes over time and how it depends on the history of similar past shocks. Moreover, investigating transitory shocks allows us to observe behavioral aspects of the response such as the persistence of changes when the relative risk levels decline, and how individuals behave when exposed to subsequent shocks.

Second, in the light of the Covid-19 pandemic, a recent strand of literature investigates the effect of information about the risk of the virus on people's beliefs, their behavioral response, and ultimately on mitigating the spread of the disease. These studies examine various channels of information provision such as Twitter, TV shows, the word of political leaders, and also experimentally provided information in different social and political environments, *e.g.* India, Mexico, Brazil, and USA. They jointly show that providing information alters people's risk perception (Fetzer et al., 2021) and significantly determines people's behavior (Ajzenman et al., 2020; Banerjee et al., 2020; Brzezinski et al., 2020; Gutierrez et al., 2020; Grossman et al., 2020). While the detailed high-frequency data in our study allow us to investigate real-time behavioral responses, the data do not enable us to study the effects of information provision on people's beliefs and their preferences. However, a change in risk perception in response to the information on a local outbreak is a one potential mechanism driving our findings. Our paper complements the aforementioned literature by providing empirical evidence on real-time behavioral responses to information on changes in the relative risk level. This allows us to get a better understanding of the adjustment trajectory of people's behavior to transitory shocks.

The paper proceeds as follows. Section 2 gives background information on the characteristics of Covid-19 and describes the experience of the pandemic in Germany including the policy responses. Section 3 presents the data and descriptive statistics. Section 4 outlines the empirical strategy. Section 5 presents the results and Section 6 concludes.

2 Background

In this section, we first give an overview of the characteristics of Covid-19 relevant to our analysis. Then we describe the experience of the pandemic in Germany including the policy responses.

2.1 Characteristics of Covid-19

The Covid-19 pandemic is a major threat to human health. According to the World Health Organization, there have been 112 million confirmed cases and 2.5 million deaths worldwide.[8] A SARS-CoV-2 infection primarily causes respiratory diseases with symptoms ranging from mild upper respiratory tract illness to severe viral pneumonia with respiratory failure and even death. At the same time, many individuals infected with the virus never develop symptoms (Huang et al., 2020). Hence, the clinical spectrum appears to be wide, encompassing asymptomatic infections, mild diseases comparable to a common cold, as well as severe lower respiratory tract diseases with many patients being hospitalized, and death (Gandhi et al., 2020). Potential long-term consequences of an infection with Covid-19, such as fatigue and dyspnoea, are currently studied (Huang et al., 2021; Zhao et al., 2020). Recent estimates suggest that the infection fatality rate (IFR) of Covid-19 is about 1%, which is substantially higher than, for example, the estimated IFR of 0.1% of influenza (Pritsch et al., 2021; Staerk et al., 2021; World Health Organization, 2020a). Particularly, the elderly population and individuals with underlying medical conditions, such as cardiovascular diseases, diabetes or chronic lung illnesses, are at risk of developing a severe course of Covid-19 infections (Centers for Disease Control and Prevention, 2021; Wu and McGoogan, 2020; Zhou et al., 2020).

Covid-19 spreads rapidly – within a couple of months, the world turned from a few reported cases in the city of Wuhan in China to a state in which almost all countries reported infections and deaths. The transmission of Covid-19 occurs from human-to-human, primarily through droplets, aerosols and close contact with infected individuals (Gandhi et al., 2020). The transmissibility of Covid-19 exhibits two disease-specific features relevant for our study: First, there is growing evidence in the medical literature that Covid-19 is an overdispersed virus, where a small fraction of individuals is responsible

[8] See `https://covid19.who.int/` accessed on 27$^{\text{th}}$ February 2021. For comparison, seasonal influenza causes worldwide approximately 300,000–500,000 deaths per year (Girard et al., 2005; Lambert and Fauci, 2010).

for a large fraction of the transmission (see e.g. Baggett et al., 2020; Endo et al., 2020; Hamner et al., 2020; James et al., 2020; Lemieux et al., 2020; Majra et al., 2021; Riou and Althaus, 2020). Second, the median incubation period before individuals feel symptoms is four to five days, with a range from 2 to up to 14 days (Gandhi et al., 2020; Lauer et al., 2020).[9]

In the absence of a Covid-19 vaccine, prevention of infections was limited to reducing the physical proximity between individuals and to wearing face masks (Chu et al., 2020; Ferguson et al., 2020).[10] A number of public health measures (NPIs) were aimed at reducing contact rates in the population and thereby mitigating the spread of the virus. Examples of the policy interventions adopted during this time include closing schools, restaurants and retail events, and contact banning.

2.2 Covid-19 Pandemic and Policy Response in Germany

At the end of January 2020, the World Health Organization declared the outbreak of the novel Coronavirus SARS-CoV-2 (i.e. Severe Acute Respiratory Syndrome Coronavirus 2) as a "public health emergency of international concern" (World Health Organization, 2020b). At this time the epicenter of the outbreak was Wuhan city, the capital of Hubei province in China. About a month later, the virus had reached Europe and started to spread uncontrolled within Germany.[11] As a consequence, the German government introduced a number of regulations to limit social contacts and thus, the diffusion of the Covid-19 virus.[12] The political response can be classified into at least four stages (Figure A1): The first stage is characterized by the increasing political and social awareness due to a growing number of local outbreaks such as in the district Heinsberg after a carnival party. To curb the spread of the virus, the government appealed to all citizens

[9] Additional information is drawn from the European Center for Disease Prevention and Control (European Centre for Disease Prevention and Control, 2021a) and from the Robert Koch Institute (Robert Koch Institut, 2021b)

[10] Note that recently some vaccines for the protection against Covid-19 have been approved. However, during the period we consider in our study no vaccines against Covid-19 were available.

[11] In Germany, COVID-19 spread after the detection of two cases on February 25, 2020. An earlier outbreak at the end of January had been completely contained.

[12] Information provided in this subsection is drawn from the German ministry of health (Bundesministerium für Gesundheit, 2021) (in German) and from the European Center for Disease Prevention and Control (European Centre for Disease Prevention and Control, 2021b).

to avoid social contacts whenever possible (e.g. Angela Merkel made nationally-televised speeches on March 12 and 18) and started to gradually impose social distancing policies. Most schools, childcare facilities, and retail stores were closed starting on March 16$^{\text{th}}$ onwards. Travel restrictions, such as enhanced controls at the borders and a 30-day entry ban for non-EU inhabitants, were enforced. The second stage is described by a national contact ban – meeting more than one person from outside one's household was prohibited, and keeping a minimum distance of 1.5 meters was required. By mid-April incidence rates started to decrease, which allowed authorities to gradually relax social distancing policies. During the third stage (May to October), incidence rates were comparatively low on the national level. Local outbreaks, however, led to temporary rises in the disease rates at the county level. One prominent example of a cluster event is the outbreak of Covid-19 in a meat processing plant in Gütersloh. The government agreed to respond locally to outbreaks, once the 7-day incidence rate within a county exceeded 50 cases per 100,000 inhabitants. Travel restrictions within the EU were largely removed during the summer months. In October, the number of local outbreaks increased rapidly, so that local policy interventions were not sufficient any more. As a response, the German government announced enhanced regulations at the national level from November, 2$^{\text{nd}}$ onwards. The fourth stage is described as so-called "lockdown light" – schools, child care facilities, and retail shops remained open, while restaurants and bars were closed.

3 Data and Descriptive Statistics

In this section, we describe the data we use to build a balanced panel for 401 districts (*i.e.* NUTS Level 3 regions) and 350 days spanning the period from January 1$^{\text{st}}$ to December 20$^{\text{th}}$, 2020 (140,350 observations).[13]

[13] Due to technical reasons, the mobility data is missing for 4 days in December.

3.1 Covid-19 Incidence Data

We use daily data on PCR positive cases of SARS-CoV-2 within Germany. The data is provided by the national public health institution, the Robert Koch Institute (RKI).[14] According to the Infectious Disease Protection Law (*Infektionsschutzgesetz*), lab-diagnosed cases of Covid-19 are reported to the local public health departments in order to monitor the temporal and spatial diffusion of the virus within Germany.[15] The reporting system follows strict rules to improve comparability across regions: Physicians and laboratories are obliged to inform local health departments about a positive test result within at most 24 hours. The date of cases in our data is the date the positive test result is reported to the local health department. The local health departments, in turn, deliver the information to the health authorities of the respective federal state with at most a one day delay. The state health department gathers the information and passes it to the Robert Koch Institute at the national level on the same or the next working day. Only reported cases that fulfill well-defined criteria are included in the data set (*Infektionsschutzgesetz, §11*). While the standardized procedure ensures high data quality, as well as comparability across time and regions, it creates a two day lag between the registration of positive test results at the local health department and publicly provided information on new Covid-19 cases by the Robert Koch Institute.[16]

The data set covers information on the day of reporting a positive PCR test result to the local health department, day of first symptoms, and the county of residence of the individual infected. Individuals are not included in the data set if they are not laboratory tested. Hence, the data likely understates the actual number of cases of Covid-19 as a

[14] The data is publicly available via COVID-19 Data Hub (COVID-19 Datenhub, 2021).

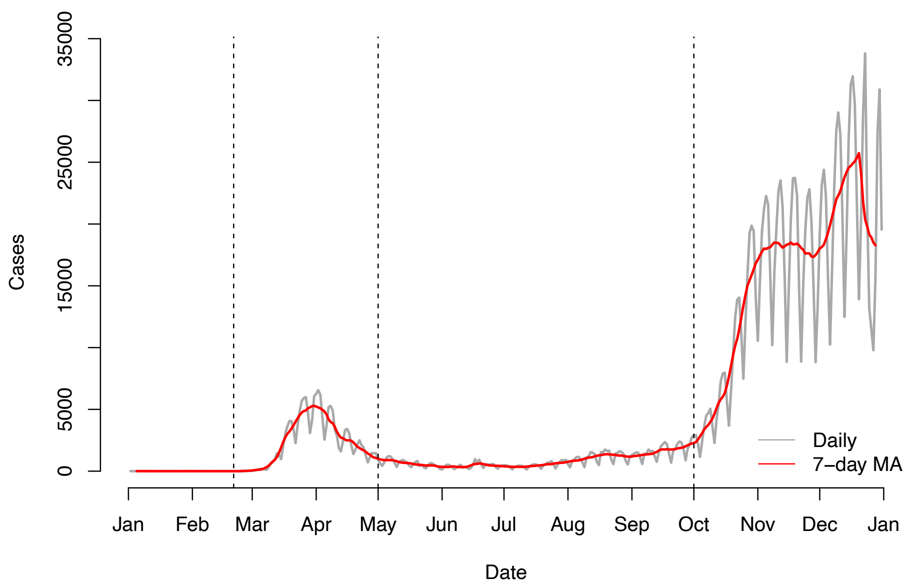
[15] The information is taken from the official webpage of the Robert Koch Institute (in German) (Robert Koch Institut, 2021a).

[16] Note that local health departments also publish information on positive test results which may create some discrepancy between information published by local health departments and the Robert Koch Institute. Nationwide newspapers such as "Bild", "Frankfurter Allgemeine Zeitung", and "Handelsblatt" use the RKI data as source for providing information on county-specific incidence rates (websites accessed on 3rd March 2021).

study conducted in Munich shows (Pritsch et al., 2021).[17]

Figure 1 illustrates the daily number of cases reported to the Robert Koch Institute between the end of February, 2020 and December, 2020. Germany experienced two waves of Covid-19 infections: The first wave started at the end of February and continued to the end of April. The second wave started in October. We classify the pandemic into three phases – 1st wave, summer, and 2nd wave – to study heterogeneous response behavior over time. Appendix Table A.1 presents the summary statistics of the new infections as counts and incidence rates separately by phase of the pandemic and by federal states.

Figure 1: Cases of Infection



Notes: The figure illustrates the daily number of cases reported cases by the Robert Koch Institute. The vertical gray lines present the different phases of the pandemic. The first phase describes the 1st wave of the pandemic between the end of February and the end of April. The second phase covers the summer months. The third phase refers to the 2nd wave of the pandemic starting in October.

[17]The study shows that in a representative sample of 2,994 private households living in Munich 1.82% individuals are tested positive for SARS-CoV-2 specific antibodies indicating that these individuals are/were infected with Covid-19. During the same time period, however, only 0.46% of the citizens in Munich have reported a positive PCR-test result to the national health agency. Hence, the reported number of cases likely understates the "true" number of individuals infected with Covid-19.

3.2 Data on Aggregate Mobility

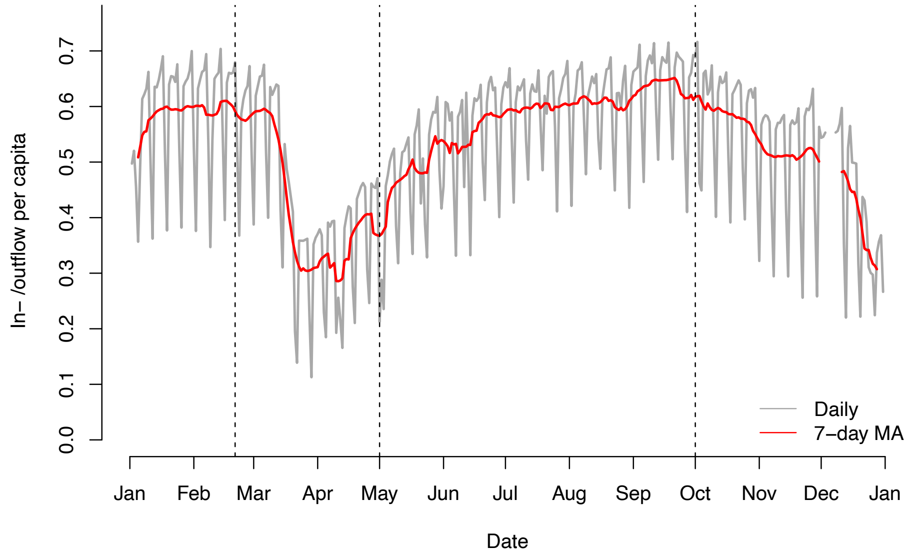
To measure mobility patterns in Germany, we use cell phone data provided on a daily basis. When cell phone users move, their phones switch between cell towers to ensure connectivity. These cell tower switches are used to estimate the number of trips taking place between two geographic areas which is a proxy of human mobility over time and space (Oliver et al., 2020). We obtain data on the daily number of trips between and within counties in Germany for the period from January 1st, 2020 to December 31st, 2020 from Teralytics, a business partner of Telefónica.[18]

Panel A in Figure 2 describes the average daily number of inflows per capita in a county between January and December 2020. By late March the number of trips decreased substantially by about 50%. During the summer months mobility patterns increased again and remained stable at a level comparable to the number of trips per capita in January and February. Starting in October, we observe a reduction in mobility again. Panel B in Figure 2 outlines the average daily number of trips within a county. The change in mobility over time follows a similar pattern as for mobility between counties. Appendix Table A.1 presents summary statistics for the number of trips per capita by phase of the pandemic and federal states.

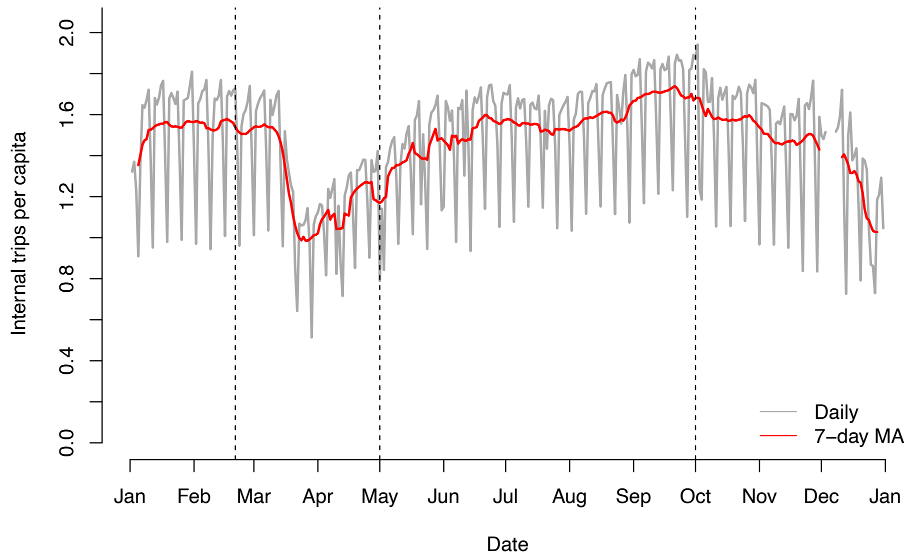
[18]Note that origin-destination pairs that have less than 5 trips taking place between them are not included int the data set. We do intentionally not extend the analysis past 2020, as the availability of vaccines, as well as the occurrence of new virus mutants likely affect behavioral responses. Hence, behavioral responses to outbreaks in 2020 are plausibly not comparable to ones in 2021.

Figure 2: Mobility Patterns

(a) Inflow/Outflow per capita



(b) Internal Trips per capita



Notes: The figures display the daily number of trips per capita (gray line) and the 7-day moving average of the number of trips (red line) between January 1st, 2020 and December 31st, 2020. Panel A illustrates the average inflow (outflow) per capita into (out of) a county. Panel B summarizes the mean number of trips per capita within a county. The vertical dashed lines outline different phases of the pandemic.

We supplement the cell phone data with laser scanner data to measure hourly mobility patterns. We obtain data from scanners counting pedestrians in 128 locations in 59 German municipalities. Most of the scanners measure pedestrian traffic on the busiest shopping and commuting streets in each town. The scanners count all pedestrians taller than 80 cm who cross an imaginary line across a street. If the same person crosses the line multiple times, each crossing is counted separately. We obtain the scanner data for the period from January 1st, 2020 to December 31st, 2020 from Hystreet.com GmbH, a company specialized in recording urban mobility patterns[19]. The advantage of the laser scanner data is that we can estimate the effects by time of day. We do not repeat the full analysis with this data as it only covers about 20% of the counties, but we find similar, although less precise, effects.

3.3 Additional Data

We supplement the data on disease incidence and mobility with information on local NPIs. Data on local NPIs in Germany is provided by an interdisciplinary consortium that works on behalf of the German Ministry of Economics and Energy.[20] The consortium collects information on NPIs based on data provided on official websites of state governments. Appendix Table A3 presents summary statistics of the NPIs considered in this study. The consortium also publishes information on county characteristics, such as the share of AfD votes, use of public transport, and the share of college educated, that we use to study heterogeneous behavior in response to local outbreaks (see Appendix Table A2 for summary statistics).

[19]We obtained the data between 18.03.2022 and 21.03.2022. The data can be downloaded for free from https://hystreet.com/.

[20]The interdisciplinary consortium comprises "infas-Institut für angewandte Sozialwissenschaft", "infas 360 GmbH" and the Institute for Hygiene and Public Health of the University of Bonn. The data sets are gathered for research purposes. For more information see https://www.corona-datenplattform.de. Accessed on 8th Feburary 2022.

4 Empirical Strategy

In this section, we describe our empirical strategy for distinguishing different sources of information, identifying unexpected outbreaks, and studying the dynamics of the aggregate behavioral response to unexpected outbreaks. We start by describing the strategy used to disentangle changes in mobility caused by different sources of information (Section 4.1). In Section 4.2, we outline a model for predicting the incidence rate in each county on each day in Germany and classify outbreaks as an excess of cases above what is predicted by the model. In Section 4.3, we present both event study and difference-in-differences models for estimating the change in mobility due to the outbreak. Section 4.4 assesses the identification strategy.

4.1 Identification of Information Sources

The timing of disease progression and delays in testing allow us to define distinct periods during which individuals receive information from two different sources: (i) Private information on people falling sick, and (ii) Public information on reported Covid-19 cases.

If a local event sparks an unexpected outbreak, individuals may obtain private information on people falling sick about 4 to 7 days (inter-quartile range) after the event (Lauer et al., 2020). Data on disease incidence, further, document that individuals get tested an average of about 5 days after first feeling symptoms. Hence, there is a delay of about a week between private information arriving based on individuals feeling sick and public information on excess cases being reported by the national public health agency.[21] Combining high-frequency data with knowledge of incubation and testing delays allows us to disentangle changes in behavior caused by private information from changes induced by public information.

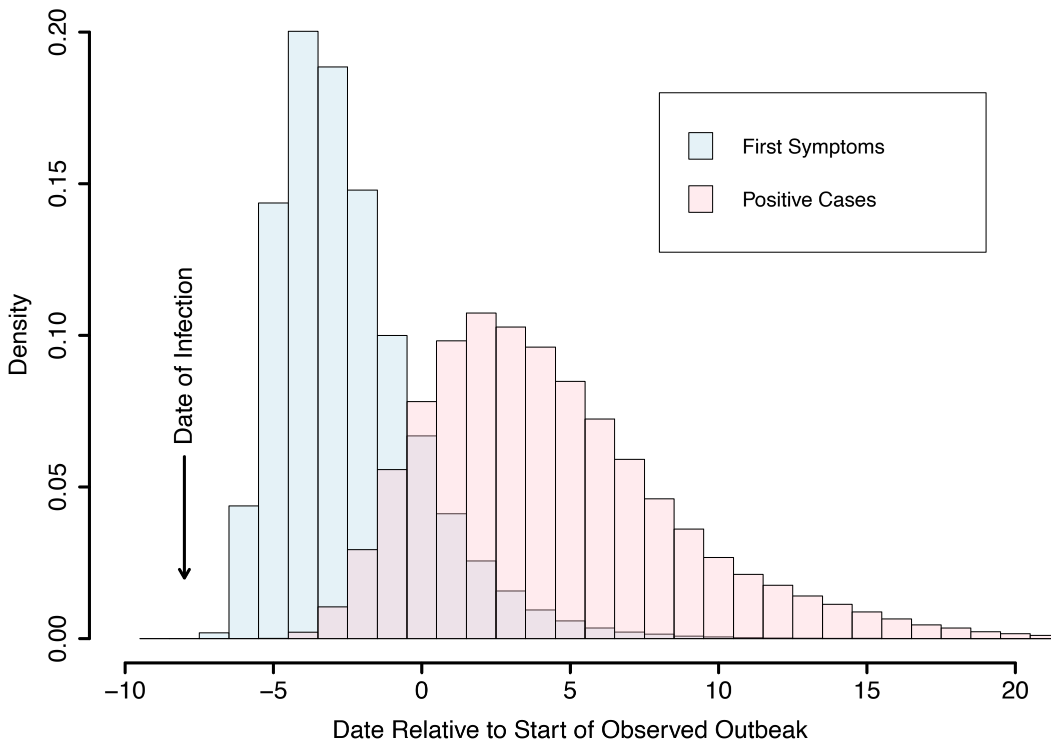
Figure 3 illustrates the timing of first symptoms and observed cases graphically. Consider an infection cluster that occurs at relative date $\Delta t = -8$. We show the distribution

[21] Recall from Section 3.1, that it takes about 2 days until the information on positive test results is passed on from the local to the national health department.

of the incubation time (*i.e.* time period between infection and first feeling symptoms) based on estimates using the log-normal distribution from Lauer et al. (2020).[22] To calculate the delay between first symptoms and cases being reported by the national public health agency, we draw on information from the RKI dataset. We define $\Delta t = 0$ as the start of the *observed* outbreak which is specified as the day of the first decile of positive cases.[23] We define the period $\Delta t \in (-7, -1)$ as the "private information" period, where behavior may change due to private information about individuals getting sick. Figure 3 shows that more than 82% of individuals feels symptoms by $\Delta t = -1$, but only 10% of the cases are reported by the national health agency at that point. The "public information" period includes the days $\Delta t \in (0, 6)$, when behavior may start to change due to excess cases being reported. Finally, we define a post period as $\Delta t \in (7, 21)$, when we expect that there is no additional information about the outbreak.[24]

[22]We use the parameter estimates in Appendix Table 2 in Lauer et al. (2020).
[23]The first decile is our approximation of the first day of excess positive test results (see Section 4.2).
[24]About 80% of observed cases have been reported by $\Delta t = 7$.

Figure 3: Timing of First Symptoms and Cases



Notes: This figure shows the distribution of the relative date of first symptoms and positive cases reported publicly for infections that occur at $\Delta t = -8$. The relative date ($\Delta t = 0$) is chosen with respect to the first decile of the positive case information. The log-normal distribution of first symptoms relative to the infection date is taken from Appendix Table 2 in Lauer et al. (2020). The delay between first symptoms and positive test results reported by the national public health agency is based on author's calculations from RKI dataset (see Section 3).

4.2 Identification of Outbreaks

We identify outbreaks by comparing the observed number of cases in a seven-day period to the number of cases predicted by a simple epidemiological model. The model used to predict the expected incidence $i_{c,s,t}$ (cases per 100,000 inhabitants) in county c, state s, day-of-the-week $dotw_t$, phase p_t, and day t is:

$$i_{c,s,t} = \sum_{j=1}^{7} \beta_j i_{c,s,t-j} + \gamma^i_{c,dotw_t,p_t} + \delta^i_{s,t} + \eta_{c,t}, \tag{1}$$

where β_j captures how the incidence depends on the seven-day incidence history in the same county. The model includes county times day-of-the-week times phase fixed effects ($\gamma^i_{c,dotw_t,p_t}$) and state times day fixed effects ($\delta^i_{s,t}$).[25] The fixed-effects account for differences in testing regimes across counties, the incidence rate in the surrounding state, and the effect of any state-level policy changes. Importantly, individuals might expect the incidence to increase in a county if the incidence is already high in the surrounding state. Our procedure identifies outbreaks that are unexpected with respect to both the history of cases in the county and the number of cases in the state.

We define an outbreak as a seven-day period where the observed incidence exceeds the expected incidence based on our simple model ($\hat{i}_{c,s,t}$). We consider two different criteria due to sampling variation when the expected number of cases is low. For counties where the expected number of cases is at least five cases per day (henceforth: *Small-count Threshold*), we take the ratio of the observed incidence to the predicted over seven days. If this ratio is greater than a threshold X, then we identify an outbreak in county c in the seven-day period (see Equation 2a, *Ratio Criterion*). As we are using count data, the ratio will be sensitive to sampling variation when the expected cases are low.[26] For this reason, we use a fixed number of cases as the threshold when the expected number of cases is

[25]County times day-of-the-week FE are allowed to vary by phase of the epidemic in Germany (1st wave, summer, 2nd wave) due to differences in testing and reporting regimes across counties and across phases. As Figure 1 shows, there is important day-of-the-week variation even in aggregate data.

[26]Consider the Poisson distribution. If the expected number of cases on a given day is five, then observing at least twice the number of cases has a probability of 1.4%. For this reason, we fix the threshold in terms of number of cases when the expected number of cases is five cases or lower. Five is the number when the Poisson probability of observing twice the number of cases is at least one percent.

below five per day on average (see Equation 2b, *Fixed Criterion*).[27] Let $I_{c,s,t} \equiv i_{c,s,t} * pop_c$ be the number of cases observed in a county, where pop_c is the population divided by 100,000 inhabitants. The decision rule is then

$$\underbrace{\frac{\sum_{j=0}^{6} i_{c,t+j}}{\sum_{j=0}^{6} \hat{i}_{c,t+j}} \geq X \quad \text{if} \quad \underbrace{\sum_{j=0}^{6} \hat{I}_{c,t+j} \geq 35}_{\text{Small-count Threshold}}}_{\text{Ratio Criterion}} \tag{2a}$$

$$\underbrace{\sum_{j=0}^{6} I_{c,t+j} \geq X * 35 \quad \text{if} \quad \underbrace{\sum_{j=0}^{6} \hat{I}_{c,t+j} < 35}_{\text{Small-count Threshold}}}_{\text{Fixed Criterion}} \ . \tag{2b}$$

In determining the threshold X, we consider different percentiles of the distribution of the ratio $\frac{\sum_{j=0,6} i_{c,t+j}}{\sum_{j=0,6} \hat{i}_{c,t+j}}$ conditional on $\sum_{j=0,6} \hat{I}_{c,t+j} \geq 35$ in the data.

Equations 2a and 2b identify the seven-day period of an outbreak. We identify the first day of excess cases (*i.e.* first day of the observed outbreak) as the first day out of the seven when the number of observed cases is above the 90$^{\text{th}}$ percentile of the Poisson distribution given the number of expected cases from the model. Finally, if two outbreaks occur within six weeks of each other in the same county, we ignore the second outbreak as it is likely part of a single large outbreak.

4.3 Event Study and Differences-in-Differences Designs

To investigate whether and to what extent information about local outbreaks affect the behavioral response, we use both event study and difference-in-differences designs. Recall from Section 4.1, that we can define three periods during which individuals may respond to different sources of information relative to first day of excess cases ($\Delta t = 0$): "private information period" ($\Delta t \in (-7, -1)$), "public information period" ($\Delta t \in (0, 6)$), and the "post period" ($\Delta t \in (7, 21)$).

The main estimation equation for outcome $y_{c,s,t}$ is

[27] We also consider small-count thresholds of four and seven in our robustness exercises and it does not affect our results. See Section 5.4.

$$y_{c,s,t} = \sum_k \alpha_k T^k_{c,t} + \mu_{c,n_{ct}} + \gamma_{c,dotw_t,p_t} + \delta_{s,t} + \boldsymbol{\lambda}' \boldsymbol{NPI}_{c,t} + \epsilon_{c,s,t}, \tag{3}$$

where we define the treatment variable $T^k_{c,t}$ differently depending if we are estimating the event study model or the difference-in-differences model. For the base event study specification, the treatment variable is defined as

$$T^k_{c,t}(\text{ES}) = D_{c,t-k} \;\text{ if } -21 \leq k \leq 21,$$

where $D_{c,t}$ is an indicator that is 1 if it is the first day of an outbreak in county c at time t and 0 otherwise. We normalize $\alpha^{\text{ES}}_{-1} = 0$. In other words, all effects are relative to the day before the first day of observed excess cases. For the difference-in-differences model, we aggregate the pre-period, public-information period, and the post-period,

$$T^k_{c,t}(\text{DiD}) = \begin{cases} \sum_{j=-21}^{-1} D_{c,t-j} & \text{if } k = 1 \\ \sum_{j=0}^{6} D_{c,t-j} & \text{if } k = 2 \\ \sum_{j=7}^{21} D_{c,t-j} & \text{if } k = 3 \end{cases},$$

where we normalize $\alpha^{\text{DiD}}_1 = 0$. In other words, all effects are relative to the period 1 to 21 days before the first day of excess cases (pre-period).

The parameters of interest are a set of dummies α_j indicating a change in mobility or reproduction rate relative to the pre-period. We include county times outbreak history fixed effects $\mu_{c,n_{ct}}$, where $n_{ct} \equiv \sum_{j=-\infty}^{-22} D_{c,t-j}$ counts the number of outbreaks that have happened at least 21 days in the past in a county.[28] We include county times day-of-the-week times phase fixed effects ($\gamma_{c,dotw_t,p_t}$), which accounts for seasonal and day of the week variation in mobility at the county level. State times day fixed effects ($\delta_{s,t}$) account for any state-level policies and seasonal variation at the state level. Finally, we include a vector of indicators on different non-pharmaceutical interventions ($\boldsymbol{NPI}_{c,t}$) at the county-day level, which accounts for policy changes that happen within states, (*e.g.*

[28]In other words, we bin the periods at the endpoints of the event windows absorbing possibly heterogeneous treatment effects for each outbreak in a county.

NPI's implemented in response to the outbreak).

As outcome variables we consider within- and between-county mobility, measured as the logarithm of the daily number of trips, and logarithm of the reproduction rate in the county. To measure between-county mobility, we sum the number of inter-county trips that begin or end in the county of interest.

4.4 Assessing the Identification Strategy

Identification is achieved within a county over time. The identifying assumption is that – conditional on the set of fixed effects – the timing of a local outbreak is exogenous.

Threats to identification include (1) county-specific time-varying unobserved characteristics (omitted variables) that correlate with outbreaks and behavior, and (2) reverse causality (*e.g.* a change in mobility patterns affects local incidence rates).

Local events (e.g. carnival, seasonal work in agriculture, private celebrations) may induce increased mobility in a particular county and thus, cause local Covid-19 outbreaks. In the case of publicly known local events, people might perceive an increased risk of infection prior to the event and, thus adjust their mobility in anticipation of an outbreak. Hence, the exogeneity assumption of local outbreaks may be violated.

To tackle the concern of potential outbreak endogeneity, we first exploit that the incubation time of Covid-19 takes on average 4 to 5 days (Gandhi et al., 2020), and the time between first symptoms and positive test results is 2 to 7 days. Individuals with knowledge of a local "risky" event (e.g. wedding, religious gathering)should start to change their behavior around the time of the event. Hence, there is plausibly a delay of at least 7 days between a change in behavior caused by knowledge of a local event and one induced by information from an increase in incidence rates. Hence, combining high frequency data with disease-specific characteristics (i.e. incubation time) allows us to disentangle changes in behavior due to a local event from ones due to information from the reported incidence rates. Second, to identify local outbreaks we use the predictions derived from the incidence model specified in Equation 1.[29] This approach allows us to

[29] See Section 4.2 for a detailed description of the identification of local outbreaks.

identify *unexpected* changes in the number of locally reported cases.

Finally, it is noteworthy that we control for local NPIs imposed in the aftermath of an outbreak. For example, child care facilities and schools were closed to curb the outbreak in a meat-processing plant in Gütersloh. Overall, we find few local NPIs were implemented in the first three weeks after an outbreak (see Appendix Figure A5) and controlling for NPIs has essentially no effect on our results (see Section 5.2).

5 Results

In this section, we present our empirical results on unanticipated outbreaks in Germany and the behavioral response to the outbreaks. Section 5.1 describes the 259 outbreaks we identify in Germany. Section 5.2 presents our main results on the behavioral response due to information about the outbreaks. Section 5.3 presents how the main effects vary by the history of outbreaks, the phase of the pandemic, and the characteristics of the counties. Finally, in Section 5.4, we discuss the sensitivity of our results to using an estimator that is robust to treatment effect heterogeneity, to using different criteria of outbreaks, and to using placebo outbreaks.

5.1 Unanticipated Covid-19 Outbreaks in Germany

We identify unanticipated outbreaks by looking for excess incidence rates relative to expected incidence rates based on a simple model that includes lagged incidence, state times day fixed effects, and county times day-of-the-week fixed effects (see Equation 1).[30] Appendix Table A4 presents the estimates of the incidence rate model. The fixed effects alone explain about 74% of the variation in the incidence rates. This is not surprising because there is a strong day-of-the-week variation in the reporting of cases and the state-level incidence rate is a good predictor of the incidence rate in the counties. Including state times day fixed effects is important as an increase in incidence rates that can be predicted by the incidence rate at the state level is unlikely to be unanticipated. The

[30]See Section 4.2 for more details.

lagged incidence rate in a county is also an important predictor of future incidence rates as can be seen in the second column of Appendix Table A4.[31] We use the incidence rate model to predict incidence rates in each county on each day.

We define an outbreak as an excess in the observed incidence rates compared to the expected from our model using Equations 2a and 2b. Appendix Figure A2 shows the distribution of the ratio of observed to expected incidence rates in the data. Our preferred threshold is the 98$^{\text{th}}$ percentile (*i.e.* $X = 1.54$), which identifies 259 outbreaks between February and November. In other words, we identify outbreaks in counties that have more than a 54% excess in a seven-day period, or more than 54 cases when the expected number of cases is less than 35 in a seven-day period ($1.54 \times 35 \approx 54$). The Ratio Criterion (*i.e.* Equation 2a) identifies 161 outbreaks and 98 are identified by the Fixed Criterion (*i.e.* Equation 2b). Table A5 shows the number of outbreaks we identify in each phase and by each criteria. More outbreaks are identified by the Ratio Criterion, except in the summer phase when incidence rates were quite low.

To better understand how unanticipated outbreaks are identified, we present the time-series figures for four well-known examples of outbreaks in Germany. Figure 4 displays the daily observed cases (blue line), the daily expected cases (green line), the earliest seven-day period that an excess is observed (grey shading), and the first day of excess cases determined by the Poisson Threshold (purple vertical line).[32]

Figure 5 shows the spatial distribution of outbreaks across Germany, while Appendix Figure A3 presents the temporal distribution of outbreaks. The outbreaks are distributed relatively evenly across the counties of Germany and across time.

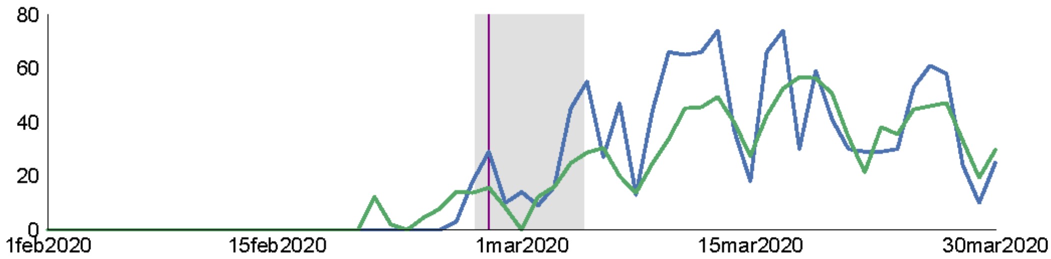
Further, we construct the distribution of the relative date of first symptoms for cases that were reported on the first day of the observed outbreak ($\Delta t = 0$). Appendix Figure A4 shows the distribution of first reported symptoms for our set of outbreaks. Most individuals with positive cases start having symptoms in the seven days before the start of the observed outbreak. This distribution further motivates our definition of the "private

[31] With the lagged incidence rates, the model explains about 78% of the variation in incidence rates.

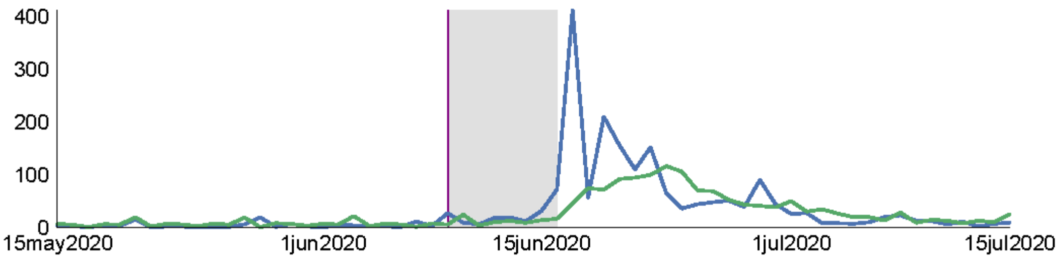
[32] Perhaps the dates chosen for Gütersloh are surprising, but it is important to note that this was a particularly large outbreak and the first day of excess cases are larger than they appear due to the differences in scale.

Figure 4: Examples of Well-known Outbreaks in Germany

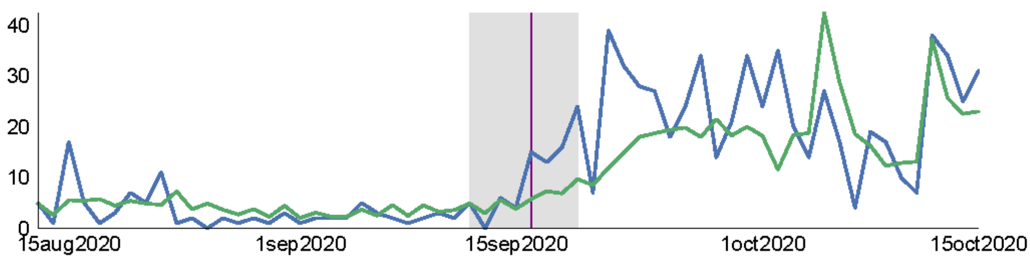
(a) March Outbreak in Heinsberg



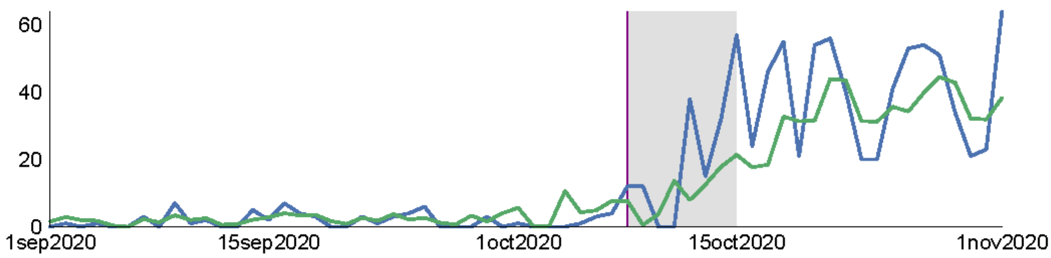
(b) June Outbreak in Gütersloh



(c) September Outbreak in Hamm

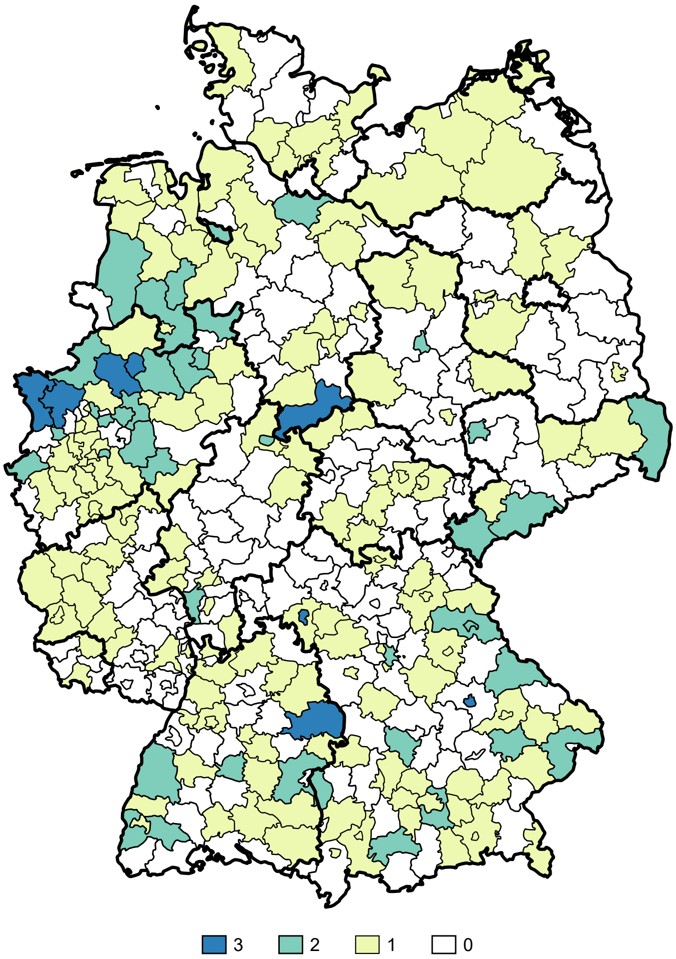


(d) October Outbreak in Berchtesgaden



Notes: These figures show four examples of well-known outbreaks that are also identified by our procedure. The blue time-series line shows the cases reported to the national public health institute on each day and the green time-series line shows the cases predicted by our model. The grey shaded area represents the seven-day period of the beginning of the outbreak and the purple vertical line shows the first date of the outbreak identified by our procedure. All four outbreaks are identified by the Ratio Criterion (Equation 2a).

Figure 5: Counties with Outbreaks



Notes: This figure shows how the outbreaks are distributed across Germany. Some counties have more than one outbreak in the February to November period.

information" period. In other words, the private information period is the period when infected individuals start to have symptoms, but when there is no public information about the outbreak yet.

Finally, we show that the outbreaks present transitory shocks–in the sense that the relative risk of infection in an outbreak county compared to the control countries dissipates after about three weeks. Appendix Figure A6 shows that the relative risk starts to decline about 7-14 days after the outbreak, by about 21 days after the outbreak the relative risk in an outbreak county is similar to the one in the control counties, and by about 28-42 days after the outbreak the relative risk in the outbreak county is even lower than in the control counties. This feature can be explained by the persistence in behavioral changes due to a local outbreak (see Section 5.2).

5.2 Behavioral Responses to Outbreaks

We now study the behavioral response to the outbreaks identified in Section 5.1. We focus on two types of outcomes. First, we have two high-frequency measures of mobility: the number of trips within a given county and the number of trips to and from a given county. The mobility outcomes give us high-frequency, direct measures of a particular kind of behavior that is not directly affected by our outbreak selection procedure. Of course, there are many types of behaviors that reduce the likelihood of infection (*e.g.* wearing masks, avoiding indoor meetings with large groups of people, social distancing in public areas). Our second type of measure is the ratio of two seven-day sums of cases in a particular county ($R_{ct} \equiv \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} / \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$), called the reproduction rate.[33] While the reproduction rate will capture the overall change in risk-avoidance behaviors of individuals, it will also be mechanically biased by the outbreak selection mechanism during the first week of the outbreak.[34] The two types of measures are complementary. While the mobility responses have information about the response at the beginning of the

[33] We use the definition of the reproduction rate applied by the Robert Koch Institut (2020). Summing cases over seven days smooths out strong day-of-the-week effects that vary by county (*e.g.* some counties do not report test results on Sundays).

[34] One can think of our outbreak selection procedure as selecting weeks where the measured reproduction rate is high.

outbreak, both measures are informative of medium and long-run changes in behavior.

Recall that due to the progression of the disease and delays in getting tested, we can interpret changes in mobility on different days as being driven by different sources of information. Let the relative date be represented by Δt, where $\Delta t = 0$ is the first day of excess cases of an outbreak. Individuals may reduce mobility due to private information about a risky event (*e.g.* a wedding or festival) in the period $\Delta t \in (-8, -6)$, due to private information about people falling ill in the period $\Delta t \in (-5, -1)$, and public information on excess cases in the period $\Delta t \in (0, 6)$.[35]

Our main results use an event study design to distinguish the effects of different sources of information on the behavioral response. Figure 6 presents the event study on the effect of an outbreak on the number of within-county trips, the number of between-county trips, and the reproduction rate. We normalize the effects relative to $\Delta t = -1$ as we do not observe any change in the three outcomes before the start of the outbreak. We shade the public-information periods, when individuals start learning about excess cases. We do not find any pre-trend in the data that may be due to knowledge of a risky event, nor do we see a significant change in mobility during the private information period. It is not until public information of the outbreak becomes available that mobility begins decline. The decrease in mobility plateaus after about seven days have passed since the first day of excess cases. The effects look similar for within-county travel and between-county travel, where the effect is a bit delayed and larger for between-county trips.

We find similar results for the reproduction rate, although we cannot interpret the estimates at the time of the outbreak. Recall from Section 4.2, that we identify outbreaks if the observed cases over a seven day period are higher than the predicted number of cases based on the previous seven days. In other words, as we are selecting counties and days where R_{ct} is high, we expect R_{ct} to mechanically increase in the first seven days of the outbreak. More generally, we expect the outbreak selection procedure to bias the results on the reproduction rate in the relative periods $\Delta t \in (-6, 15)$, with the bias being quite

[35]If a risky event is large enough, we may observe an increase in mobility at the time of the event.

large for $\Delta t \in (0, 6)$.[36] Notice though that the pre-trend is quite flat for $\Delta t < -7$. As in the mobility data, we see a significant decrease in the reproduction rate after $\Delta t > 15$. In summary, we don't find any evidence from the estimates on mobility or the reproduction rate that individuals are anticipating the outbreaks. Moreover, the mobility data show that individuals are quite responsive to high-frequency risk information as they start to modify their behavior only a few days after the start of an outbreak. Finally, we find that individuals decrease their mobility after an outbreak and this partly explains the substantial decrease in the reproduction rate. All three figures show that the effects are quite persistent, which is something we investigate in more detail shortly.

We quantify the average effect by estimating the difference-in-differences specification, shown in Table 1. The estimates are normalized relative to the period $\Delta t \in (-21, -1)$. In order to understand if local NPIs are driving our results, we present results with and without controlling for local NPIs. We find that controlling for NPIs makes little difference in our estimates.[37] The average mobility effect in the public-information period is between a third to half of the full effect in the post period as individuals are learning about and adapting to the outbreak. Again, the reproduction rate is substantially higher in the first seven days of the outbreak reflecting our selection of outbreaks. In the medium run, unexpected outbreaks significantly decrease within- and between-county mobility by about 2.4 percent and 2.6 percent, respectively. While this may seem like a small change, the overall effect is quite large when considering the reproduction rate. The reproduction rate significantly declines by about 0.33 after an outbreak.[38] In Table 2, we investigate the persistence of these effects by extending the window an additional three weeks.[39] We find that the effects on mobility are quite persistent, where the decline in mobility has not

[36] The estimates will be biased downward for $\Delta t \in (-6, -1)$ as you might expect from selection since these dates are used for predicting cases and appear in the denominator of the Ratio Criterion (see Section 4.2). The bias is expected to be large and positive in the outbreak period ($\Delta t \in (0, 6)$). Remember the calculation of R_{ct} includes cases in (t,t-6) in the numerator, so we expect that R_{ct} could be biased upwards by the selection mechanism until $\Delta t = 12$. Finally, one might expect that R_{ct} would likewise be biased downwards for $\Delta t \in (9, 15)$ as part of the outbreak is still included in the denominator of R_{ct}.

[37] Note that NPIs are set almost exclusively at the state level in Germany and, hence, the effect of NPIs are being absorbed by the state times day fixed effects. Indeed, we show in Appendix Figure A5 that there is little increase in the number of NPIs after an outbreak.

[38] The average decline in the reproduction rate is similar if we restrict the post-period to $\Delta t \in (16, 21)$.

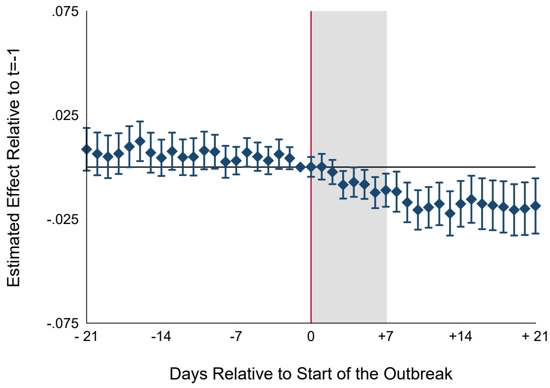
[39] The corresponding event study figures can be seen in Appendix Figure A7.

changed 42 days after an outbreak. While the decline in the reproduction rate is smaller, the average effect of a decrease of 0.25 in the reproduction rate is still substantial 42 days after the outbreak.

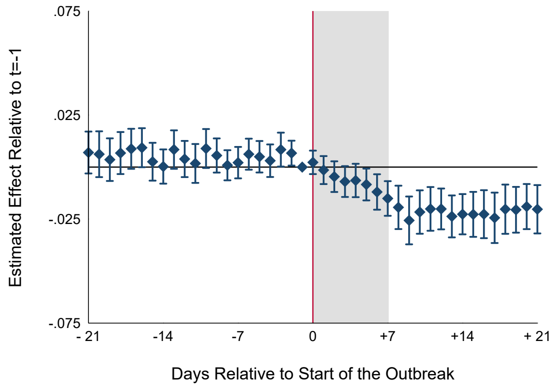
One concern is that the behavioral changes are not voluntary responses, but are driven by work-from-home policies at the firms in the county. While it is difficult to rule this out with our data, we investigate how the effects vary by hour of the day using the laser scanner data described in Section 3.2. To the extent that the laser scanner data is representative of overall mobility in a county, we can investigate whether the overall behavioral response is being driven by changes in mobility during commuting hours. Appendix Figure A11 shows the event study pooling the day into six hour periods. Appendix Figure A12 shows how the difference-in-differences estimates vary by hour of the day. We don't find evidence that the overall behavioral response in the laser scanner data is being driven by changes during commuting hours.

Figure 6: Event Studies of the Behavioral Response to Outbreaks

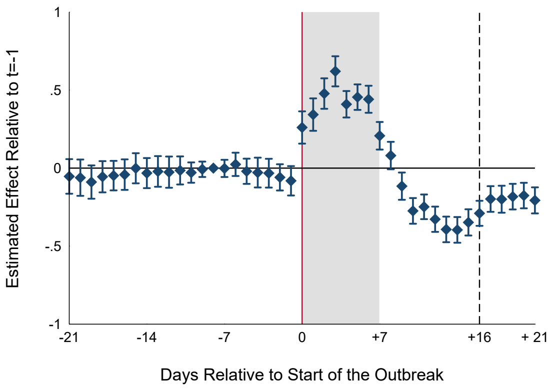
(a) Trips Within Outbreak County



(b) Trips To/From Other Counties



(c) Reproduction Rate ($\log R_{ct}$)



Notes: County-level event studies of the log number of trips taken within a county with an outbreak (Panel a), log number of trips taken between the outbreak county and other counties (Panel b), and the log reproduction rate in a county $R_{ct} \equiv \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Panel c). The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3 for more information). Time $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The shaded area represents the seven-day period when the excess of cases is observed and information about the outbreak is revealed by the public health authorities. The dashed line in Panel c reflects the point at which the calculation of R_{ct} is no longer mechanically affected by the outbreak selection. Event studies showing longer post periods are shown in Appendix Figure A7.

Table 1: Difference-in-Difference Estimates of the Behavioral Response to Outbreaks

	Within County		**Between County**		**Reproduction Rate**	
Public Information	-0.0114**	-0.0112**	-0.0104**	-0.0103**	0.4620***	0.4610***
$\Delta \in$ (0,6)	(0.004)	(0.004)	(0.004)	(0.004)	(0.016)	(0.026)
Post-Period	-0.0239***	-0.0234***	-0.0266***	-0.0261***	-0.1699***	-0.1711***
$\Delta \in$ (7,21)	(0.005)	(0.005)	(0.005)	(0.005)	(0.014)	(0.021)
Observations	140350	140350	140350	140350	100359	100359
Adj.R2.	0.994	0.994	0.992	0.992	0.187	0.164
NPI FE	No	Yes	No	Yes	No	Yes

Notes: This table presents the difference-in-difference estimates of the event studies shown in Figure 6. The dependent variables are the log number of trips taken within a county with an outbreak (Columns 2 and 3), the log number of trips taken between the outbreak county and other counties (Columns 4 and 5), and the log reproduction rate in a county $R_{ct} \equiv \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Columns 6 and 7). Public Information refers to the seven-day period ($\Delta t \in (0,6)$) when the excess of cases is observed and information about the outbreak is revealed by the public health authorities. The Post Period refers to $\Delta t \in (7,21)$, where $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The estimates are normalized relative to the period $\Delta t \in (-21,-1)$. The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Standard errors are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Comparing Short-Run and Long-Run Difference-in-Difference Estimates of the Behavioral Response to Outbreaks

	Within County		**Between County**		**Reproduction Rate**	
Public Information	-0.0111**	-0.0109**	-0.0098**	-0.0097*	0.4619***	0.4604***
$\Delta \in$ (0,6)	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0257)	(0.0256)
Post Period	-0.0239***	-0.0235***	-0.0261***	-0.0257***	-0.1745***	-0.1765***
$\Delta t \in (0,6)$	(0.0055)	(0.0055)	(0.0052)	(0.0052)	(0.0201)	(0.0204)
Post Period	-0.0257***	-0.0254***	-0.0254***	-0.0250***	-0.1033***	-0.1050***
$\Delta \in$ (22,42)	(0.0073)	(0.0072)	(0.0063)	(0.0063)	(0.0221)	(0.0223)
Observations	140349	140349	140349	140349	100358	100358
Adj.R2.	0.994	0.994	0.992	0.992	0.163	0.164
NPI FE	No	Yes	No	Yes	No	Yes

Notes: This table presents the difference-in-difference estimates of the event studies shown in Appendix Figure A7. The dependent variables are the log number of trips taken within a county with an outbreak (Columns 2 and 3), the log number of trips taken between the outbreak county and other counties (Columns 4 and 5), and the log reproduction rate in a county $R_{ct} \equiv \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Columns 6 and 7). Public Information refers to the seven-day period ($\Delta t \in (0,6)$) when the excess of cases is observed and information about the outbreak is revealed by the public health authorities. The Post Period refers to $\Delta t \in (7,21)$, where $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The estimates are normalized relative to the period $\Delta t \in (-21,-1)$. The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Standard errors are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.3 Heterogeneity in Behavioral Responses

There are a number of reasons why the mobility response to an outbreak may vary across counties and across time. Counties may differ in the average costs of reducing mobility (*e.g.* more factory workers than programmers), mobility may expose populations in certain counties to greater risk (*e.g.* higher usage of subways than cars), or the average beliefs about the risk of the virus may vary across populations. In the following, we provide suggestive evidence on each of the three channels.

Table 3 shows how effects vary by stage of the pandemic and history of outbreaks. It also shows how effects vary with level of urbanization of the county. Table 4 shows how effects vary by continuous proxies: share of college educated, hotel beds per capita, public transportation trips per capita, and share of voters who voted for the party AfD in the last state election. The continuous variables are standardized with mean zero and standard deviation one to ease interpretation and comparability of the results.

Investigating the response to information about transitory shocks allows us to provide evidence about the types of costs facing individuals as they adjust their behavior. Columns 2-4 in Table 3 show the response for the first outbreak and then subsequent outbreaks in a county, as well as how the response varies by phase of the pandemic. Focusing on the first outbreak in a county, we see that mobility declines by between 2-3% in the first wave, about 1% in the summer, and about 4.5% in the second wave. We interpret these results as showing that "pandemic fatigue" was not important in the mobility response to unanticipated outbreaks.[40] Interestingly, the mobility response for subsequent outbreaks in the summer is 1.6-2%, and then not significant in the second wave. That the mobility response in the second wave is strongest for the first outbreak and consistent with zero for subsequent outbreaks is suggestive of important fixed costs to adjusting mobility. The response in the reproduction rate is consistent with fatigue or increasing marginal costs. The response is strongest for first outbreaks in the first wave

[40]The response may have been weaker during the summer as people were less attentive when the national incidence rate was low. For example, a simple query in google trends for "rki corona" or "rki corona fallzahlen" shows that the number of searches in Germany about the coronavirus were higher during the first and second wave compared to the summer period, reaching four to five times higher at the peaks in the middle of our first and third phases.

with the reproduction rate decreasing by 0.45. The response in reproduction rate to a first outbreak decreases to 0.38 in the summer and 0.27 in the second wave. Likewise the response is lower for subsequent outbreaks, where it is about 0.23 in the summer and second wave. These results along with the evidence on persistence of responses in the previous section are suggestive of important fixed costs in changing behavior, especially when it comes to mobility. We do find that other types of behavior, as evidenced by the reproduction rate, may have important marginal costs that increase with the number of shocks and the length of the pandemic.

The costs of adjusting mobility may vary if a large share of workers can work from home, if a large share of the mobility is discretionary, or if individuals are tired of restrictions on mobility. We investigate each of these in turn. If the likelihood of being able to work from home is larger for college-educated workers, then we may expect the effects to be larger in counties where the fraction of individuals with tertiary degrees is higher. Interestingly, we do not find that the effect on within-county mobility changes depends on education. The effect for between-county mobility is stronger in counties with a higher fraction of individuals with a tertiary degree. The effect is fifty percent larger in a county with a one standard deviation higher share of tertiary degrees.

Trips taken due to tourism or business travel may be easier to reduce compared to other kinds of trips, like commuting to work. We study how the effects vary by the importance of the travel industry in a county, proxied by hotel beds per capita. Indeed, we find that the effect of an outbreak on mobility is much larger in counties where the travel industry is important. Counties with one standard deviation more hotel beds per capita have mobility effects that are two and a half times larger for within-county travel and twice as large for between-county travel.

If the average risk of a trip is higher, we may expect the mobility response to be larger. The average risk may be larger in counties with higher usage of public transportation or in counties with a higher population density. Interestingly, as seen in Table 4, we do not find that the mobility response depends on the number of public transportation trips per capita. In Table 3, we separately estimate the effects for four different categories of population density. We do find that the effects are larger in "Large Cities" and do not find a significant effect in "Cities" and "Rural Areas with Small Cities".[41] Paradoxically, we find equally large effects in the "Rural" areas—least dense category—as in "Large Cities". Many of the rural counties in our sample are also places with high levels of tourism. If we control for the interaction with hotel beds per capita, we find that the mobility response in rural areas decreases by half, while it increases in cities. We interpret this as evidence that the increased effect in rural areas is mostly due to the lower costs of discretionary travel, while the effect in cities is consistent with the increased risk of a higher population density.

Beliefs about the risk of Covid-19 in a county may lead to stronger or weaker responses to an outbreak. A number of studies in the US (e.g. Andersen, 2020; Allcott et al., 2020; Barrios and Hochberg, 2020; Grossman et al., 2020; Painter and Qiu, 2020) have shown how counties with higher Republican support were less likely to change their behavior in response to Covid-19. Similarly in Germany, the AfD party was critical of the government handling of Covid-19 and one may conjecture that counties with high AfD vote shares would, likewise, respond less to an outbreak. In line with the findings in the US, we provide evidence that the reproduction rate decreases less in counties with a larger AfD vote share in response to an outbreak. Mobility patterns, however, are not affected at a significant level by the AfD vote share.

Finally, we separately estimate the effects for the outbreaks determined by two outbreak criteria (see Section 4.2). In other words, we check to see if the response is the same in counties with fewer than 35 expected cases at the time of the outbreak and counties with more than 35 cases at the time of the outbreak. On the one hand, we find that the *mobility* responses to outbreaks identified by the Ratio Criterion (Equation 2a) and outbreaks identified by the Fixed Criterion (Equation 2b) are nearly the same (see

[41]We refer to the classification into different types of urbanization proposed by Kuhlmann (2019). "Large Cities" denote *Kreisfreie Großstädte* with more 100,000 inhabitants. "Cities" present *Städtische Kreise* with a population density of at least 150 inhabitants/km^2 and at least 50% of the population living in a city. "Rural Areas with Small Cities" include (i) counties with a population density less than 150 inhabitants/km^2 and at least 50% of the population living in a city and (ii) counties with a population density of at least 100 inhabitants/km^2 and less 50% of the population living in a city. "Rural Areas" denote counties with a population density smaller than 100 inhabitants/km^2 and less than 50% of the population living in a city.

Appendix Table A9). On the other hand, the reduction in the reproduction rate is much larger in counties with few expected cases, -0.25 (-.45) in counties with more (less) than 35 expected cases over a seven day period at the time of an outbreak. Note that the calculation of the reproduction rate only considers the cases in a given county and does not account for across-county spread. The difference in response may reflect that the actions of individuals in a given county have a smaller measured effect on the reproduction rate when there are higher rates of infection from other counties.

Table 3: Heterogeneity Analysis: Part I

	Outbreak Number and Phase			**Type of Urbanization**					
	Within	**Between**	$\log R_{ct}$	**Within**	**Between**	$\log R_{ct}$	**Within**	**Between**	$\log R_{ct}$
Post Period - 1st Outbreak × 1st Wave	-0.021*	-0.028**	-0.133***						
	(0.008)	(0.009)	(0.033)						
Post Period - 1st Outbreak × Summer	-0.013*	-0.010	-0.247***						
	(0.006)	(0.007)	(0.049)						
Post Period - 1st Outbreak × 2nd Wave	-0.046**	-0.044***	-0.202***						
	(0.016)	(0.012)	(0.036)						
Post Period - Subsequent Outbreak(s) × Summer	-0.016**	-0.020**	-0.182***						
	(0.006)	(0.007)	(0.049)						
Post Period - Subsequent Outbreak(s) × 2nd Wave	0.003	-0.009	-0.126*						
	(0.008)	(0.009)	(0.050)						
Post Period - 1st Outbreak × Large Cities				-0.034***	-0.041***	-0.166***	-0.054***	-0.058***	-0.167***
				(0.010)	(0.012)	(0.033)	(0.011)	(0.013)	(0.037)
Post Period - 1st Outbreak × Cities				-0.003	-0.008	-0.142***	-0.011	-0.014*	-0.135***
				(0.005)	(0.005)	(0.030)	(0.007)	(0.006)	(0.032)
Post Period - 1st Outbreak × Rural Small Cities				-0.027**	-0.024*	-0.181***	-0.017*	-0.016	-0.177***
				(0.010)	(0.011)	(0.046)	(0.009)	(0.010)	(0.052)
Post Period - 1st Outbreak × Rural				-0.044**	-0.045***	-0.218***	-0.021	-0.027**	-0.234***
				(0.016)	(0.012)	(0.044)	(0.011)	(0.009)	(0.050)
Observations	140350	140350	100359	140350	140350	100359	140350	140350	100359
Adj.R2.	0.994	0.992	0.163	0.994	0.992	0.162	0.994	0.992	0.164
FE				Yes	Yes	Yes	Yes	Yes	Yes
Period × Hotel Beds Interaction	No	No	No	No	No	No	Yes	Yes	Yes

Notes: This table studies heterogeneity in the behavioral response to local outbreaks relative to the base difference-in-difference estimates in Table 1. Columns 2-4 consider heterogeneity by phase and whether an outbreak was the first in a county. Columns 5-10 considers heterogeneity due to the level of urbanization of the county. The models with urbanization are estimated additionally controlling for interactions with the standardized "hotel beds per capita" variable from Table 4 (Columns 11-13). The Post Period refers to $\Delta t \in (7, 21)$, where $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The estimates are normalized relative to the period $\Delta t \in (-21, -1)$. The estimates for the "Public Information" period $\Delta t \in (0, 6)$ and the corresponding interactions are not shown. The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Standard errors are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Heterogeneity Analysis: Part II

	Tertiary School Degree			Public Transport			AFD Vote Share			Hotel Beds Per Capita		
	Within	**Between**	log R_{ct}	**Within**	**Between**	log R_{ct}	**Within**	**Between**	log R_{ct}	**Within**	**Between**	log R_{ct}
Post Period	-0.0231***	-0.0253***	-0.1714***	-0.0235***	-0.0257***	-0.1707***	-0.0221***	-0.0249***	-0.1622***	-0.0242***	-0.0267***	-0.1714***
	(0.005)	(0.005)	(0.021)	(0.005)	(0.005)	(0.021)	(0.005)	(0.005)	(0.021)	(0.005)	(0.005)	(0.022)
Post Period× Tertiary School Degree	-0.0048	-0.0127**	0.0070									
	(0.004)	(0.005)	(0.017)									
Post Period× Public Transport				0.0013	-0.0060	0.0158						
				(0.005)	(0.006)	(0.018)						
Post Period× AfD Vote Share							0.0051	0.0047	0.0402			
							(0.007)	(0.006)	(0.024)			
Post Period× Hotel Beds per Capita										-0.0395***	-0.0293***	-0.0061
										(0.009)	(0.006)	(0.019)
Observations	140350	140350	100359	140350	140350	100359	140350	140350	100359	140350	140350	100359
Adj.R2.	0.994	0.992	0.164	0.994	0.992	0.164	0.994	0.992	0.164	0.994	0.992	0.164
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table studies heterogeneity in the behavioral response to local outbreaks relative to the base difference-in-difference estimates in Table 1. Columns 2-4 consider heterogeneity by the share of individuals with a tertiary school degree in a county. Columns 5-7 consider heterogeneity by public transportation per capita inhabitants, Columns 8-10 on the vote share for AfD in the last state elections. Columns 11-13 study differences in the response to the number of hotel beds per capita in a county. All four variables are standardized to have zero mean and standard deviation of 1.0. The Post Period refers to $\Delta t \in (7, 21)$ relative to the first day of excess cases in the outbreak (see Section 4.2). The estimates for the "Public Information" period $\Delta t \in (0, 6)$ and the corresponding interactions are not shown. The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Standard errors are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.4 Sensitivity Analysis

We estimate a number of alternative specifications to understand the robustness of our results.

Alternative DiD Estimator by De Chaisemartin and d'Haultfoeuille (2020) A fast-growing body of literature shows that two-way fixed effects regressions provide consistent estimates only under the assumption of effect homogeneity (e.g. Goodman-Bacon, 2021; Borusyak et al., 2021; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). In staggered roll-outs, already-treated units will act as controls for later-treated units (Goodman-Bacon, 2021). If treatment effects are heterogeneous over time and across groups, two-way fixed effect models provide inconsistent estimates for the average treatment effect (ATE).

To address concerns about the reliability of DiD estimators in the presence of effect heterogeneity, we replicate our findings by using the alternative DiD estimator proposed by De Chaisemartin and d'Haultfoeuille (2020) which compares the outcome evolution of groups being treated for the first time and not yet treated groups.

Appendix Figure A9 and Appendix Figure A10 show that our main results presented in Section 5.2 are nearly identical to the ones produced using the alternative DiD estimator proposed by De Chaisemartin and d'Haultfoeuille (2020). We did not expect our estimates to have large biases in our setting for three reasons. First, we have a large number of never treated units, where about half of the counties never experience an outbreak (see Section 5.1). Second, our empirical strategy includes county times outbreak history fixed effects which absorb persistent county-specific behavior changes outside of the event-study window (see Section 4.3). Third, the fraction of counties that have overlapping event study windows (*i.e.* the remaining source of potential bias from effect heterogeneity) is small relative to the total number of counties in our sample.

Definition of Outbreaks We run a number of robustness checks showing that our findings are not sensitive to the definition of outbreaks (see Section 4.2 for more information on the definition of outbreaks).

We vary the X-threshold (97th, 98th, and 99th percentiles, Appendix Table A11) and the small-count threshold (four, five, and seven expected cases per day, Appendix Table A12) for identifying outbreaks. Appendix Table A10 shows the number of outbreaks identified using the different thresholds and for the different criteria, where the number of outbreaks identified varies from 140 to 353. We estimate the difference-in-differences model using each of these sets of outbreaks in Appendix Table A11 and Appendix Table A12. Lowering the X-threshold leads to slightly lower estimates for the effect, but the difference with preferred specification is negligible. Increasing the X-threshold on the other hand, leads to a substantial increase in the estimated effects. The higher X-threshold only includes larger outbreaks, and so it may not be surprising that the responses are larger in this case (Appendix Table A11). The estimated effect is smaller when lowering the small-sample threshold, this is expected as we are introducing some outbreaks that are the being identified from the small-count noise. The estimated effects when raising the small-count threshold are nearly the same as our preferred specification (Appendix Table A12).

Placebo We perform a placebo study, where, for each outbreak in the data, we replace the county identifier with a randomly chosen county and then repeat the analysis. Appendix Figure A8 shows the event study analysis using placebo outbreaks and Table A8 show the Difference-in-Difference estimates. We do not find any effect in the placebo outbreak sample.

6 Conclusion

This paper underscores the importance of public information as a policy tool for mitigating public health risks. We study this in the context of Covid-19, where behavioral responses have been important to contain the spread of the virus and, hence, the costs of the pandemic. To identify behavioral responses induced by public information versus other sources, we combine high-frequency data with facts about the incubation period of Covid-19 and reporting time in Germany. We first develop a simple epidemiological model that allows us to identify unexpected local outbreaks by comparing the observed number of cases to the expected number. Based on the model, we find 259 outbreaks at the county level that are distributed relatively evenly across the counties in Germany and across time. Using an event-study design on local unexpected outbreaks, we find that mobility significantly decreases by about 2.5% in response to public information about the outbreak, while private knowledge about people falling sick does not appear to cause a change in behavior. We also find substantial changes in the reproduction rate after an outbreak of about 0.33. Both behavioral responses are quite persistent and depend on the history of outbreaks in a county and the stage of the pandemic. In addition, there are important heterogeneities in the behavioral responses, where responses are stronger in counties with high population density, with more hotels per capita, and with a higher share of college educated. These findings are consistent with behavioral changes depending on the relative risk and costs of changing mobility.

This paper demonstrates that providing high-frequency localized information on health risks is an important tool in the toolbox of public health policy makers. Individuals quickly respond to unanticipated changes in risk levels and the responses persist even when the change in relative risk levels dissipates. The persistence of behavioral changes points to important fixed costs, which may be behavioral in nature (*e.g.* habit formation), may involve private costs (*e.g.* setting up a home office) or may be due to institutional rule changes (*e.g.* employers changing work-from-home policies). Understanding the sources of these fixed costs is an important element in designing effective public health policies. The presence of fixed costs also means that researchers need to account for the history of policies and shocks experienced by individuals when constructing models of risk-avoidance behavior. Likewise, attempts to understand the effectiveness of different policies will depend on these histories and may help explain the large variation in estimates of NPIs in different countries and contexts.

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A Appendix

A.1 Summary Statistics

Table A1: Summary Statistics Part I: Infections and Trips

				New infections, mean (std.dev.)		Trips per capita, mean (std.dev.)		
State	# of counties	Phase	Obs	Cases	Incidence	Outgoing	Incoming	Internal
All states	401	before	20,050			0.68 (0.29)	0.68 (0.29)	1.46 (0.41)
		1st wave	28,070	5.79 (13.25)	2.83 (5.18)	0.50 (0.26)	0.50 (0.26)	1.24 (0.39)
		summer	61,353	2.15 (6.76)	0.89 (1.94)	0.68 (0.28)	0.68 (0.28)	1.54 (0.48)
		2nd wave	36,892	39.57 (73.07)	18.21 (17.63)	0.61 (0.28)	0.61 (0.28)	1.46 (0.45)
Baden-Würtemberg	44	before	2,200			0.62 (0.26)	0.62 (0.26)	1.55 (0.40)
		1st wave	3,080	10.51 (15.05)	4.47 (6.27)	0.44 (0.23)	0.44 (0.23)	1.29 (0.37)
		summer	6,732	2.64 (4.43)	1.00 (1.47)	0.59 (0.23)	0.59 (0.23)	1.52 (0.38)
		2nd wave	4,048	47.47 (45.58)	18.66 (14.32)	0.54 (0.25)	0.54 (0.24)	1.52 (0.43)
Bayern	96	before	4,800			0.91 (0.33)	0.90 (0.33)	1.42 (0.45)
		1st wave	6,720	6.40 (14.60)	4.71 (7.87)	0.64 (0.32)	0.63 (0.32)	1.16 (0.41)
		summer	14,688	1.76 (6.15)	1.12 (2.59)	0.89 (0.31)	0.89 (0.30)	1.50 (0.53)
		2nd wave	8,832	29.59 (50.69)	20.95 (17.92)	0.81 (0.34)	0.81 (0.33)	1.43 (0.45)
Berlin	1	before	50			0.22 (0.04)	0.22 (0.03)	1.78 (0.29)
		1st wave	70	84.97 (76.02)	2.33 (2.09)	0.16 (0.05)	0.16 (0.05)	1.35 (0.38)
		summer	153	58.86 (52.57)	1.61 (1.44)	0.22 (0.04)	0.21 (0.03)	1.56 (0.28)
		2nd wave	92	903.95 (501.08)	24.80 (13.75)	0.19 (0.04)	0.18 (0.04)	1.46 (0.30)
Brandenburg	18	before	900			0.74 (0.26)	0.72 (0.24)	1.40 (0.48)
		1st wave	1,260	2.33 (5.19)	1.43 (2.89)	0.59 (0.24)	0.59 (0.24)	1.30 (0.47)
		summer	2,754	0.52 (1.32)	0.34 (0.86)	0.86 (0.26)	0.86 (0.26)	1.75 (0.64)
		2nd wave	1,656	23.51 (26.81)	17.48 (20.80)	0.73 (0.25)	0.73 (0.25)	1.72 (0.65)
Bremen	2	before	100			0.57 (0.14)	0.56 (0.13)	1.52 (0.29)
		1st wave	140	6.46 (12.65)	1.40 (2.28)	0.43 (0.17)	0.42 (0.16)	1.21 (0.32)
		summer	306	5.11 (7.63)	1.41 (2.06)	0.52 (0.14)	0.52 (0.14)	1.40 (0.26)
		2nd wave	184	60.88 (67.49)	14.79 (10.71)	0.49 (0.17)	0.49 (0.16)	1.35 (0.30)
Hamburg	1	before	50			0.32 (0.06)	0.32 (0.05)	1.73 (0.31)
		1st wave	70	69.36 (60.72)	3.77 (3.30)	0.22 (0.09)	0.22 (0.08)	1.28 (0.33)
		summer	153	20.89 (23.52)	1.13 (1.28)	0.29 (0.06)	0.28 (0.05)	1.51 (0.29)
		2nd wave	92	319.12 (158.07)	17.33 (8.59)	0.25 (0.06)	0.25 (0.06)	1.42 (0.32)
Hessen	26	before	1,300			0.60 (0.22)	0.61 (0.22)	1.40 (0.37)
		1st wave	1,820	4.61 (6.89)	1.97 (2.91)	0.44 (0.20)	0.45 (0.20)	1.18 (0.33)
		summer	3,978	2.72 (5.04)	1.03 (1.54)	0.58 (0.19)	0.58 (0.19)	1.44 (0.36)
		2nd wave	2,392	49.97 (52.73)	19.83 (15.60)	0.52 (0.19)	0.52 (0.19)	1.37 (0.38)
Mecklenburg-Vorpommern	8	before	400			0.50 (0.22)	0.49 (0.22)	1.72 (0.39)

		1st wave	560	1.24 (2.13)	0.67 (1.28)	0.41 (0.21)	0.40 (0.21)	1.53 (0.41)
		summer	1,224	0.43 (1.21)	0.22 (0.68)	0.69 (0.24)	0.68 (0.25)	2.50 (0.91)
		2nd wave	736	15.04 (17.74)	7.49 (8.72)	0.53 (0.24)	0.52 (0.25)	2.02 (0.68)
Niedersachsen	45	before	2,250			0.60 (0.22)	0.60 (0.22)	1.47 (0.39)
		1st wave	3,150	3.28 (7.55)	1.58 (2.80)	0.46 (0.21)	0.46 (0.21)	1.25 (0.37)
		summer	6,885	1.49 (4.08)	0.72 (1.57)	0.60 (0.21)	0.60 (0.21)	1.52 (0.41)
		2nd wave	4,140	21.52 (34.56)	11.40 (11.57)	0.54 (0.22)	0.54 (0.22)	1.46 (0.42)
Nordrhein-Westfalen	53	before	2,650			0.53 (0.16)	0.53 (0.15)	1.61 (0.34)
		1st wave	3,710	8.92 (13.33)	2.65 (3.58)	0.38 (0.16)	0.39 (0.16)	1.32 (0.33)
		summer	8,109	4.67 (9.01)	1.35 (2.47)	0.50 (0.14)	0.50 (0.14)	1.56 (0.32)
		2nd wave	4,876	66.93 (59.47)	19.86 (13.85)	0.44 (0.14)	0.44 (0.14)	1.43 (0.35)
Rheinland-Pfalz	36	before	1,800			0.79 (0.27)	0.79 (0.26)	1.26 (0.33)
		1st wave	2,520	2.41 (3.83)	2.07 (3.12)	0.59 (0.25)	0.59 (0.25)	1.07 (0.28)
		summer	5,508	0.87 (1.96)	0.71 (1.46)	0.80 (0.24)	0.80 (0.23)	1.32 (0.34)
		2nd wave	3,312	18.87 (19.88)	16.38 (14.65)	0.70 (0.24)	0.70 (0.24)	1.22 (0.35)
Saarland	6	before	300			0.61 (0.17)	0.61 (0.17)	1.47 (0.31)
		1st wave	420	6.05 (11.36)	3.24 (4.52)	0.43 (0.18)	0.43 (0.18)	1.16 (0.30)
		summer	918	0.90 (1.62)	0.54 (0.95)	0.59 (0.17)	0.59 (0.17)	1.44 (0.30)
		2nd wave	552	30.23 (32.74)	17.53 (12.92)	0.54 (0.18)	0.54 (0.18)	1.39 (0.31)
Sachsen	13	before	650			0.49 (0.18)	0.49 (0.18)	1.54 (0.37)
		1st wave	910	5.20 (7.78)	1.66 (2.43)	0.39 (0.19)	0.39 (0.19)	1.36 (0.38)
		summer	1,989	1.39 (2.94)	0.45 (1.02)	0.53 (0.19)	0.53 (0.20)	1.66 (0.39)
		2nd wave	1,196	108.95 (103.10)	36.29 (34.21)	0.46 (0.20)	0.46 (0.20)	1.59 (0.44)
Sachsen-Anhalt	14	before	700			0.53 (0.21)	0.54 (0.21)	1.65 (0.46)
		1st wave	980	1.60 (3.15)	0.97 (1.77)	0.45 (0.20)	0.45 (0.20)	1.51 (0.43)
		summer	2,142	0.53 (1.45)	0.31 (0.78)	0.58 (0.20)	0.59 (0.21)	1.79 (0.46)
		2nd wave	1,288	22.01 (25.58)	13.86 (15.46)	0.53 (0.22)	0.54 (0.22)	1.73 (0.49)
Schleswig-Holstein	15	before	750			0.59 (0.19)	0.58 (0.18)	1.38 (0.30)
		1st wave	1,050	2.58 (4.77)	1.21 (1.99)	0.43 (0.19)	0.43 (0.19)	1.17 (0.31)
		summer	2,295	0.93 (2.16)	0.49 (1.33)	0.61 (0.19)	0.60 (0.18)	1.55 (0.50)
		2nd wave	1,380	14.71 (17.52)	7.04 (7.00)	0.53 (0.19)	0.52 (0.19)	1.38 (0.38)
Thüringen	23	before	1,150			0.60 (0.21)	0.60 (0.21)	1.35 (0.43)
		1st wave	1,610	1.45 (2.87)	1.52 (2.92)	0.48 (0.21)	0.49 (0.21)	1.22 (0.39)
		summer	3,519	0.51 (1.38)	0.58 (1.69)	0.63 (0.21)	0.63 (0.22)	1.43 (0.42)
		2nd wave	2,116	18.66 (22.98)	20.67 (25.26)	0.57 (0.23)	0.58 (0.23)	1.41 (0.43)

Notes: The table reports the mean and standard deviation of the set of variables included in the analysis. The data is pooled over the period of observation and counties (N=401). Incidence is defined as the daily number of cases per 100,000 inhabitants.

Table A2: Summary Statistics Part II: Additional Variables

	Mean	**S.D.**
No. of Beds in Hotels per Capita	4.26	5.24
Public Transport per Capita	0.29	0.09
Share of Tertiary Degree	11.85	3.23
Vote Share AfD	12.47	6.15
Large Cities	0.17	0.37
Cities	0.33	0.47
Rural Areas w/ Small Cities	0.25	0.43
Rural Areas	0.25	0.44

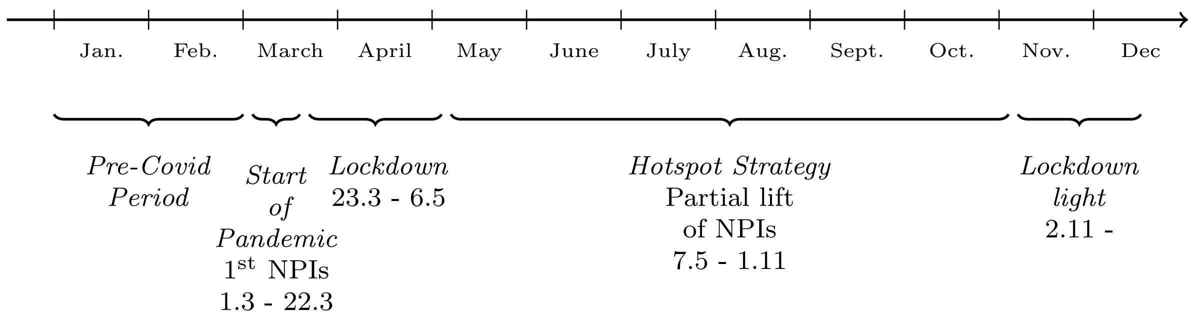
Notes: This table reports mean and standard deviation of variables used in the heterogeneity analysis. The data are cross-sectional and provided at the county level.

Table A3: Summary Statistics Part III: Non-Pharmaceutical Interventions

	1st Wave		Summer		2nd Wave	
	Mean	SD	Mean	SD	Mean	SD
Child Care, School and Work						
Day Care	0.35	0.48	0.66	0.47	0.86	0.35
Primary Schools	0.42	0.49	0.89	0.31	0.91	0.29
Secondary Schools	0.35	0.48	0.91	0.28	0.92	0.27
Workplace	0.07	0.26	0.24	0.42	0.13	0.34
Travel						
Travel Restrictions Domestic	0.12	0.33	0.13	0.34	0.00	0.00
Travel Restrictions Foreign	0.04	0.20	0.00	0.00	0.00	0.00
Public Transport	0.00	0.00	0.00	0.00	0.00	0.00
General NPIs						
Mask Mandate	0.09	0.29	0.99	0.10	1.00	0.00
Social Distancing	0.45	0.50	0.87	0.34	0.95	0.22
Exit Restrictions	0.15	0.35	0.05	0.21	0.09	0.29
Contacts - Private Space	0.19	0.39	0.57	0.49	0.76	0.42
Contacts - Public Space	0.41	0.49	0.99	0.07	0.98	0.13
Testing	0.02	0.14	0.12	0.33	0.08	0.27
Service, Hotels, Restaurants						
Services	0.52	0.50	0.99	0.07	0.99	0.07
Hotels	0.52	0.50	0.96	0.20	0.93	0.25
Restaurants	0.57	0.50	1.00	0.00	0.97	0.18
Retails	0.49	0.50	0.91	0.28	0.97	0.16
Events, Sports and Culture						
Events Indoor	0.56	0.50	0.99	0.08	0.98	0.13
Events Outdoor	0.57	0.50	0.97	0.17	0.99	0.11
Night Life	0.55	0.50	1.00	0.00	1.00	0.02
Sports Indoor	0.55	0.50	0.96	0.20	0.96	0.19
Sports Outdoor	0.55	0.50	0.94	0.23	0.93	0.25
Culture and Education	0.54	0.50	0.96	0.20	0.97	0.16
Observations	28070		61353		36892	

Notes: This table reports mean and standard deviation of the NPIs considered in this study, by phase of the pandemic. The variables present the fraction of days a particular NPI was in place.

Figure A1: Periods of the Covid-Pandemic in Germany



Notes: The figure illustrates different periods of political response to the spread of Covid-19 in Germany.

A.2 Supplementary Information on the Identification of Outbreaks

Table A4: Incidence Model

		Incidence Rates$_t$
Incidence Rate$_{t-1}$		0.1465***
		(0.011)
Incidence Rate$_{t-2}$		0.0921***
		(0.011)
Incidence Rate$_{t-3}$		0.0956***
		(0.009)
Incidence Rate$_{t-4}$		0.0945***
		(0.011)
Incidence Rate$_{t-5}$		0.0709***
		(0.011)
Incidence Rate$_{t-6}$		0.0971***
		(0.009)
Incidence Rate$_{t-7}$		0.0468***
		(0.012)
Observations	131127	131127
Adj.R2.	0.742	0.777
FE	Yes	Yes

Notes: The table displays the estimates of Equation 1 in the text. Column 1 includes county times day-of-the-week times phase fixed effects ($\gamma^i_{c,dotw_t,p_t}$) and state times day fixed effects (δ^i_{st}). In Column 2, we additionally control for lagged incidence rates.

Table A5: Summary of Outbreaks Identified

	No. of Outbreaks		
	Total	**Identified by Eq. 2a**	**Identified by Eq. 2b**
1st Wave	105	77	28
Summer	80	36	44
2nd Wave	74	48	26
Total	259	161	98

Notes: The table summarizes the number of outbreaks per phase of the pandemic. Column 1 presents the total number of outbreaks per phase. Column 2 and 3 display the number of outbreaks identified by Equation 2a and Equation 2b, respectively.

Table A6: Summary Statistics Part V: Number of Outbreaks per Phase and Outbreak Number

	1st Wave	**Summer**	**2nd Wave**	**Total**
1st Outbreak	104	43	57	204
2nd Outbreak	1	34	12	47
3rd Outbreak	0	3	5	8
Total	105	80	74	259

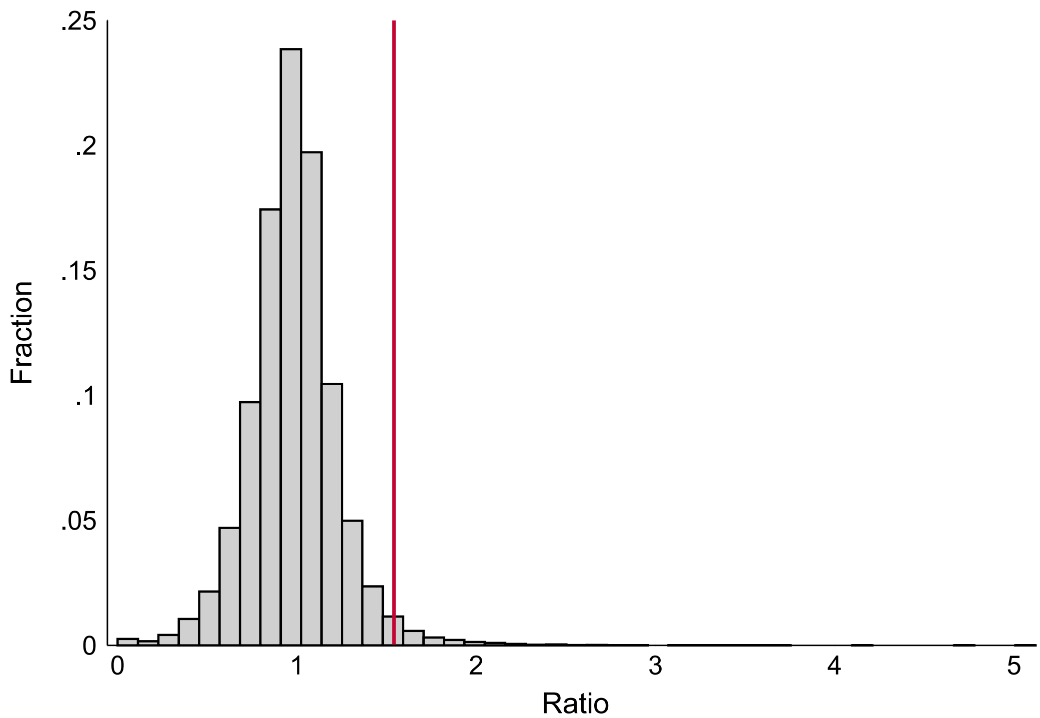
Notes: The table summarizes the number of first, second, and third outbreaks within a county per phase of the pandemic.

Table A7: Summary Statistics Part IV: Comparison of Counties with at least one Outbreak to Counties without Outbreak

	With Outbreak		Without Outbreak		
	Mean	SD	Mean	SD	P-Value
Population Size	226064.33	174914.58	187320.25	298207.18	0.11
Population Density	605.36	783.91	459.59	600.37	0.04
Large Cities	0.22	0.42	0.11	0.32	0.00
Cities	0.34	0.48	0.31	0.46	0.48
Rural with Small Cities	0.21	0.41	0.29	0.46	0.05
Rural	0.23	0.42	0.28	0.45	0.18
Share with Tertiary Degree	12.08	3.63	11.62	2.76	0.16
Mean Age	44.15	1.82	44.94	2.03	0.00
Unemployment Rate	5.31	2.41	5.41	2.42	0.67
Observations	204		197		401

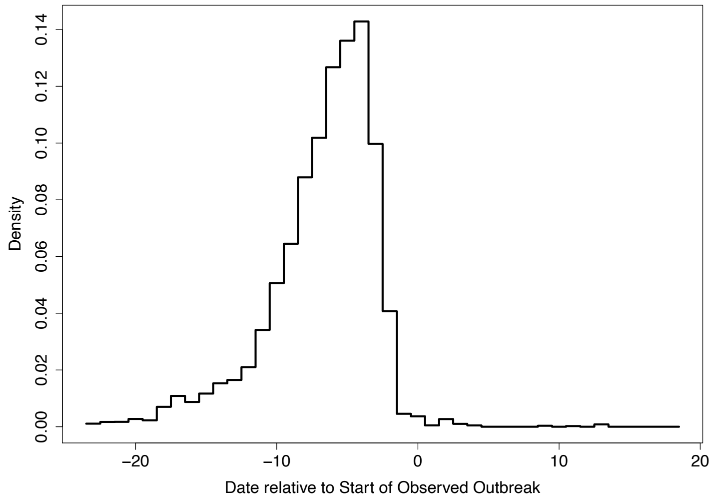
Notes: The table summarizes the mean and standard deviation in counties with at least one outbreak (Columns 1 and 2) and in counties without any identified outbreak (Columns 3 and 4). Column 5 reports the p-value of the differences in means between counties with at least one outbreak and ones without any outbreak.

Figure A2: Distribution of the 7-Day Incidence Rate Relative to the Expected 7-day Incidence Rate



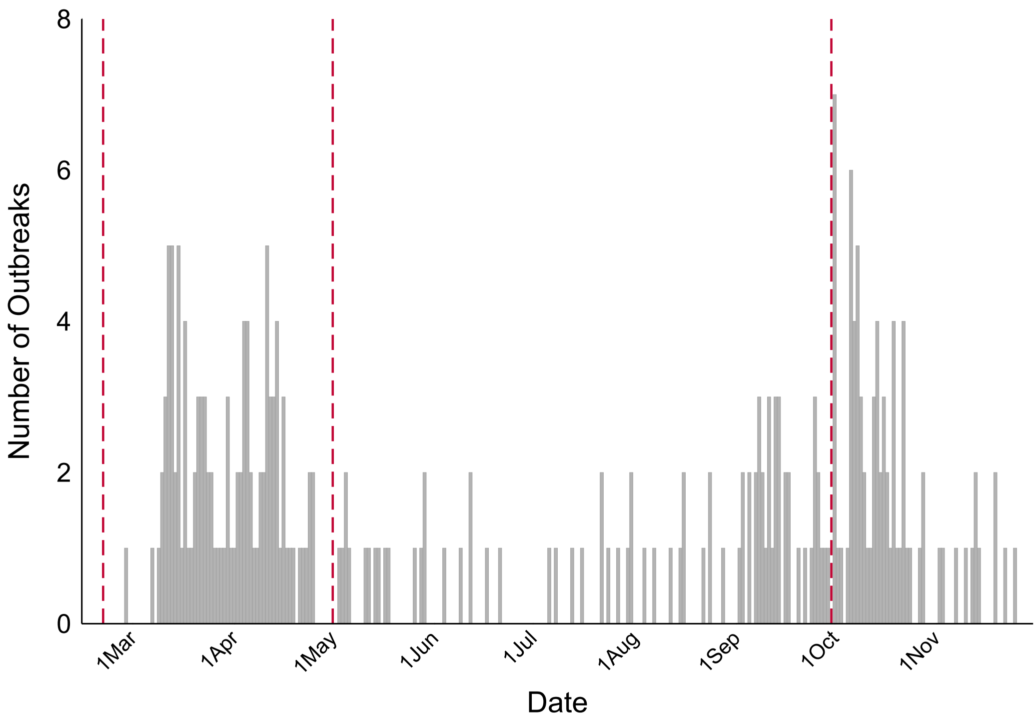
Notes: The figure illustrates the empirical distribution of the 7-day incidence rates relative to the expected 7-day incidence rates if the number of expected cases within that 7 day window exceeds 35. The red line displays the 98$^{\text{th}}$ percentile threshold.

Figure A4: Distribution of First Symptoms



Notes: This figure shows the distribution of the relative date of first symptoms for the cases that were reported on the first day of the observed outbreaks ($\Delta t = 0$). Note that the relative date includes a two-day delay between individuals getting tested and the cases being publicly reported by the national public health agency (See Section 3).

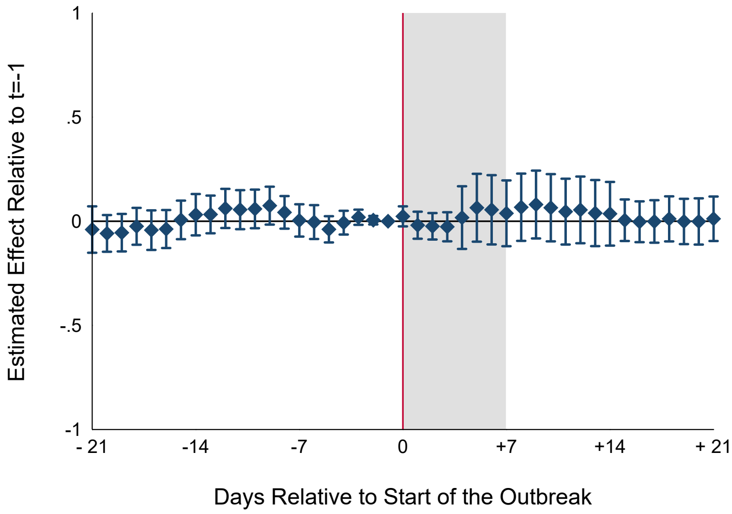
Figure A3: Distribution of Outbreaks, per Day



Notes: The figure illustrates the number of outbreaks per day. The red dash vertical lines represent the classification into the phases of the pandemic.

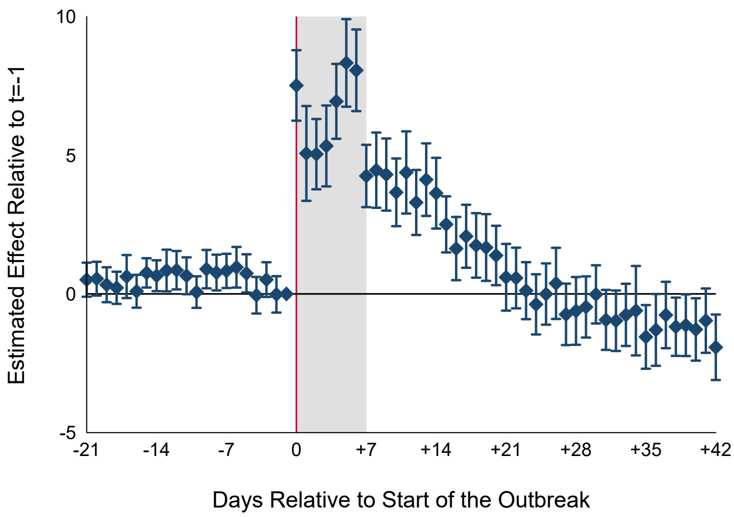
A.3 Sensitivity of Results

Figure A5: Event Study of the Local Policy Responses to Outbreaks



Notes: County-level event study of the number of local NPIs implemented in a county. The model controls for day times state fixed effects, and county times day-of-the-week fixed effects (see Section 4.3 for more information). Time $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The shaded area represents the seven-day period when the excess of cases is observed and information about the outbreak is revealed by the public health authorities.

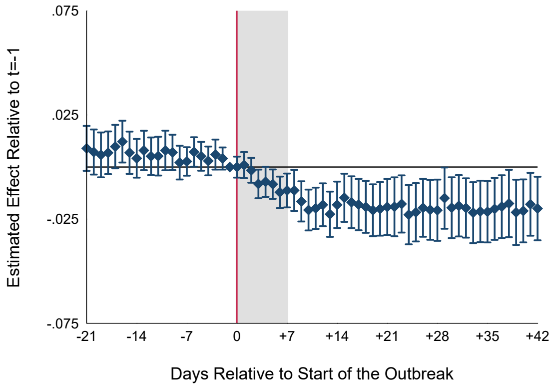
Figure A6: Event Study of the Incidence Rates to Outbreaks



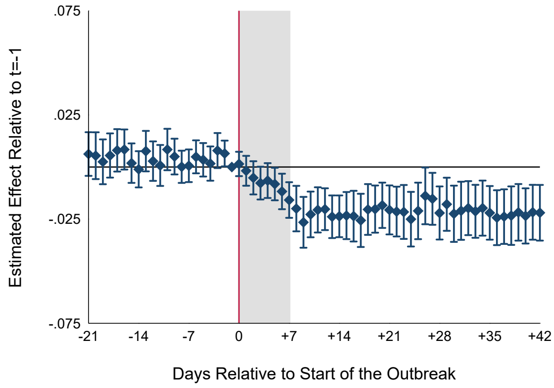
Notes: County-level event study of incidence rates (*i.e.* cases per 100,000 inhabitants) in a county. The model controls for day times state fixed effects, and county times day-of-the-week fixed effects (see Section 4.3 for more information). Time $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The shaded area represents the seven-day period when the excess of cases is observed and information about the outbreak is revealed by the public health authorities.

Figure A7: Event Studies of the Behavioral Response to Outbreaks - Long Post-Outbreak Window

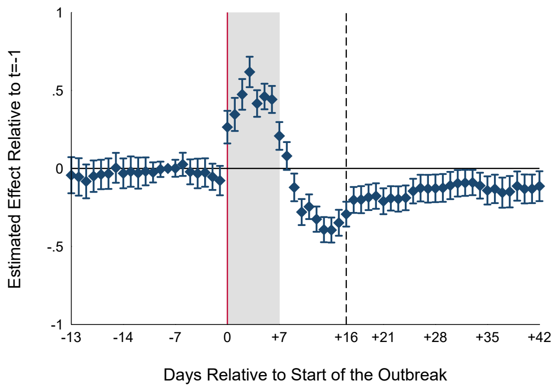
(a) Trips Within Outbreak County



(b) Trips To/From Other Counties



(c) Reproduction Rate ($\log R_{ct}$)



Notes: County-level event studies of the log number of trips taken within a county with an outbreak (Panel a), log number of trips taken between the outbreak county and other counties (Panel b), and log of the reproduction rate in a county $\log(R_{ct}) = \log\left(\sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}\right)$ (Panel c). The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Time $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The shaded area represents the seven-day period when the excess of cases is observed and information about the outbreak is revealed by the public health authorities. The dashed line in Panel c reflects the point at which the calculation of R_{ct} is no longer mechanically affected by the outbreak selection.

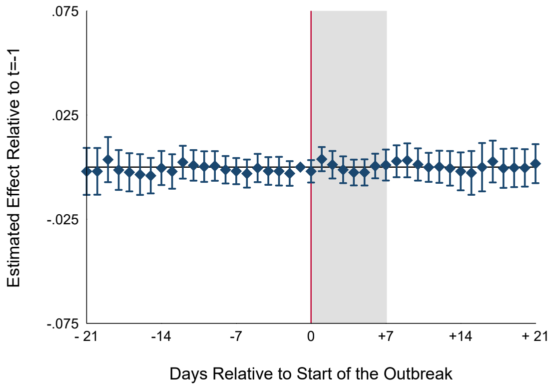
Table A8: Difference-in-Difference Estimates of the Behavioral Response to *Placebo* Outbreaks

	Within County	**Between County**	$\log R_{ct}$
Post-Period	0.0016	-0.0013	-0.0296
	(0.004)	(0.004)	(0.023)
Observations	140350	140350	100358
Adj.R2.	0.994	0.992	0.149
NPI FE	Yes	Yes	Yes

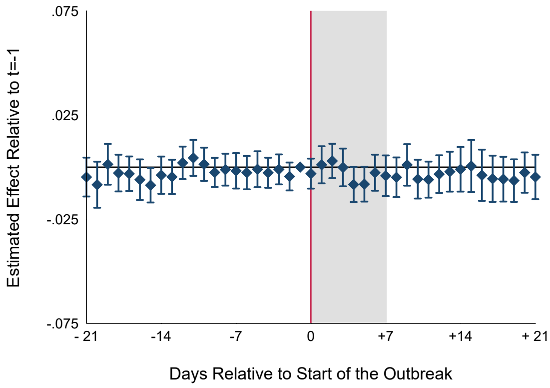
Notes: This table presents the difference-in-difference estimates of the event studies using "Placebo" Outbreaks shown in Appendix Figure A8. Placebo outbreaks are assigned the same dates as actual outbreaks, but are randomly assigned to a different county. The dependent variables are the log number of trips taken within a county with an outbreak (Column 2), the log number of trips taken between the outbreak county and other counties (Column 3), and the log reproduction rate in a county $R_{ct} = \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Column 4). The Post Period refers to $\Delta t \in (7, 21)$, where $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The estimates are normalized relative to the period $\Delta t \in (-21, -1)$. The estimates for the "Public Information" period $\Delta t \in (0, 6)$ are not shown. The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Standard errors are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A8: Event Studies of the Behavioral Response to *Placebo* Outbreaks

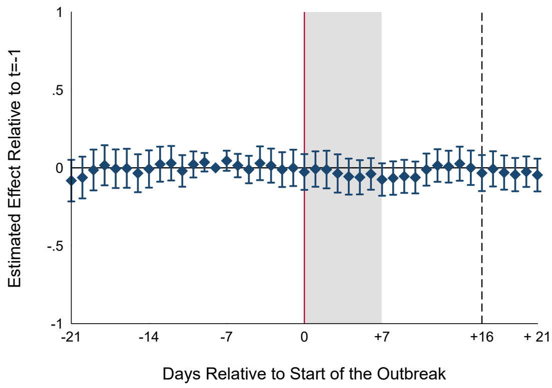
(a) Trips Within Outbreak County



(b) Trips To/From Other Counties



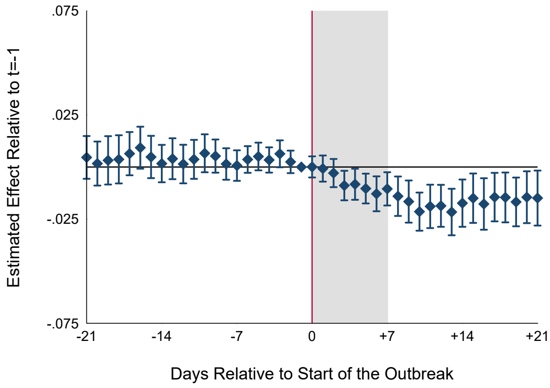
(c) Reproduction Rate (log R_{ct})



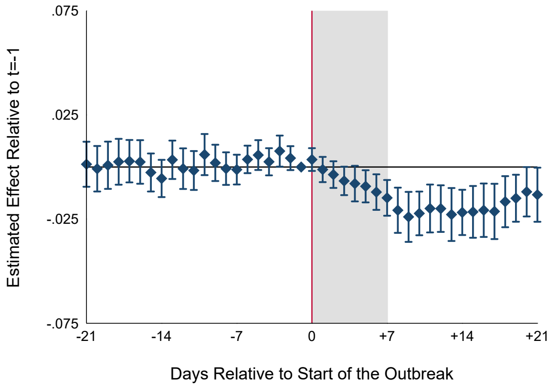
Notes: County-level event studies using "placebo" outbreaks. Placebo outbreaks are assigned the same dates as actual outbreaks, but are randomly assigned to a different county. The panels show the log number of trips taken within a county with a placebo outbreak (Panel a), log number of trips taken between the placebo outbreak county and other counties (Panel b), and the log reproduction rate in a county $R_{ct} = \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Panel c). The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Time $\Delta t = 0$ is the first day of excess cases of the outbreak (see Section 4.2). The shaded area represents the seven-day period when the excess of cases is observed and information about the outbreak would be revealed by the public health authorities. The dashed line in Panel c reflects the point at which the calculation of R_{ct} would no longer be mechanically affected by the outbreak selection.

Figure A9: Event Studies of the Behavioral Response to Outbreaks
De Chaisemartin and d'Haultfoeuille (2020) Estimator

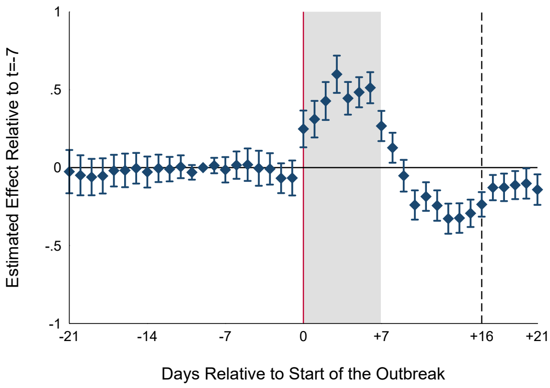
(a) Trips Within Outbreak County



(b) Trips To/From Other Counties



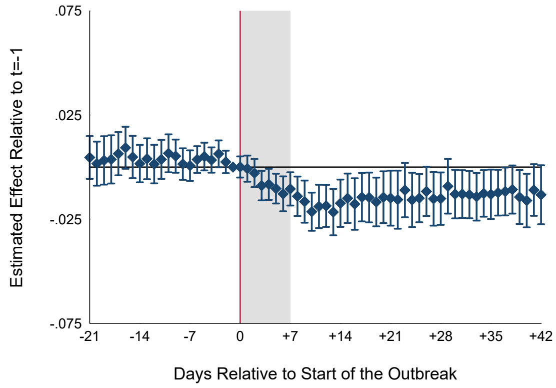
(c) Reproduction Rate ($\log R_{ct}$)



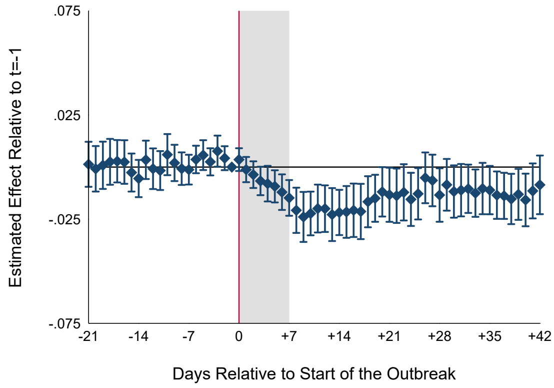
Notes: County-level event studies of the log number of trips taken within a county with an outbreak (Panel a), log number of trips taken between the outbreak county and other counties (Panel b), and the log reproduction rate in a county $R_{ct} = \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Panel c). The outcomes are first regressed on controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). The residuals of the regression are then used as the dependent variable in the De Chaisemartin and d'Haultfoeuille (2020) estimator (see Section 5.4). Time $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The shaded area represents the seven-day period when the excess of cases is observed and information about the outbreak is revealed by the public health authorities. The dashed line in Panel c reflects the point at which the calculation of R_{ct} is no longer mechanically affected by the outbreak selection. Event studies showing longer post periods are shown in Appendix Figure A10.

Figure A10: Event Studies of the Behavioral Response to Outbreaks
De Chaisemartin and d'Haultfoeuille (2020) Estimator - Long Post-Outbreak Window

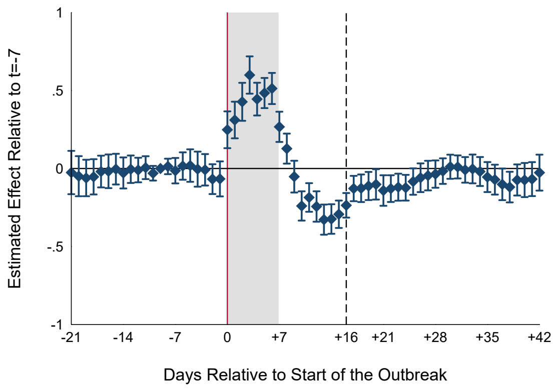
(a) Trips Within County



(b) Trips To/From Other Counties



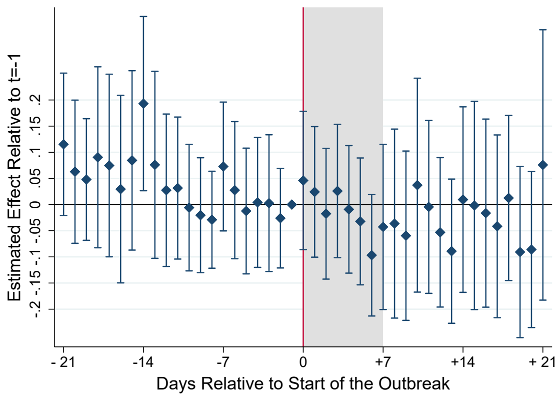
(c) Reproduction Rate ($\log R_{ct}$)



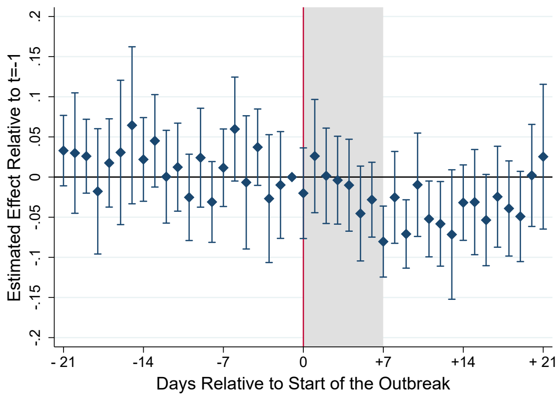
Notes: County-level event studies of the log number of trips taken within a county with an outbreak (Panel a), log number of trips taken between the outbreak county and other counties (Panel b), and the log reproduction rate in a county $R_{ct} = \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Panel c). The outcomes are first regressed on controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). The residuals of the regression are then used as the dependent variable in the De Chaisemartin and d'Haultfoeuille (2020) estimator (see Section 5.4). Time $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The shaded area represents the seven-day period when the excess of cases is observed and information about the outbreak is revealed by the public health authorities. The dashed line in Panel c reflects the point at which the calculation of R_{ct} is no longer mechanically affected by the outbreak selection.

Figure A11: Event Studies of the Behavioral Response to Outbreaks - Pedestrian Data

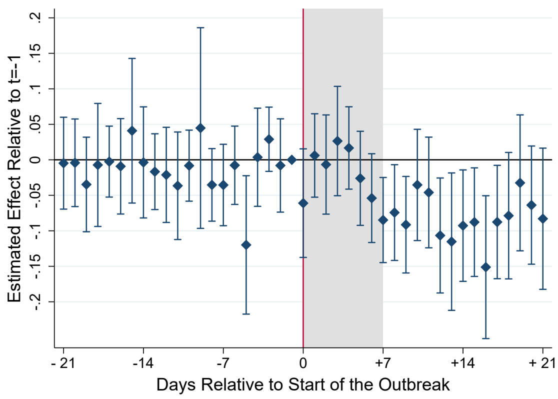
(a) Between 0:00 and 6:00



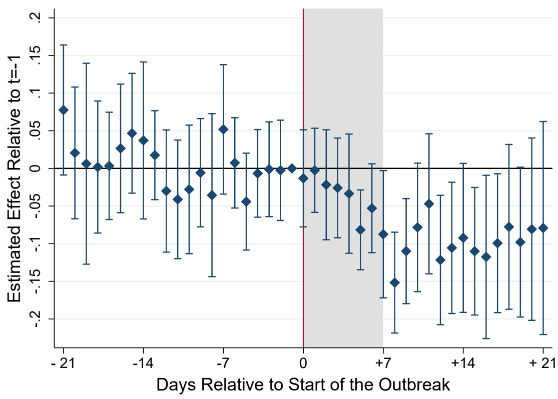
(b) Between 6:00 and 12:00



(c) Between 12:00 and 18:00

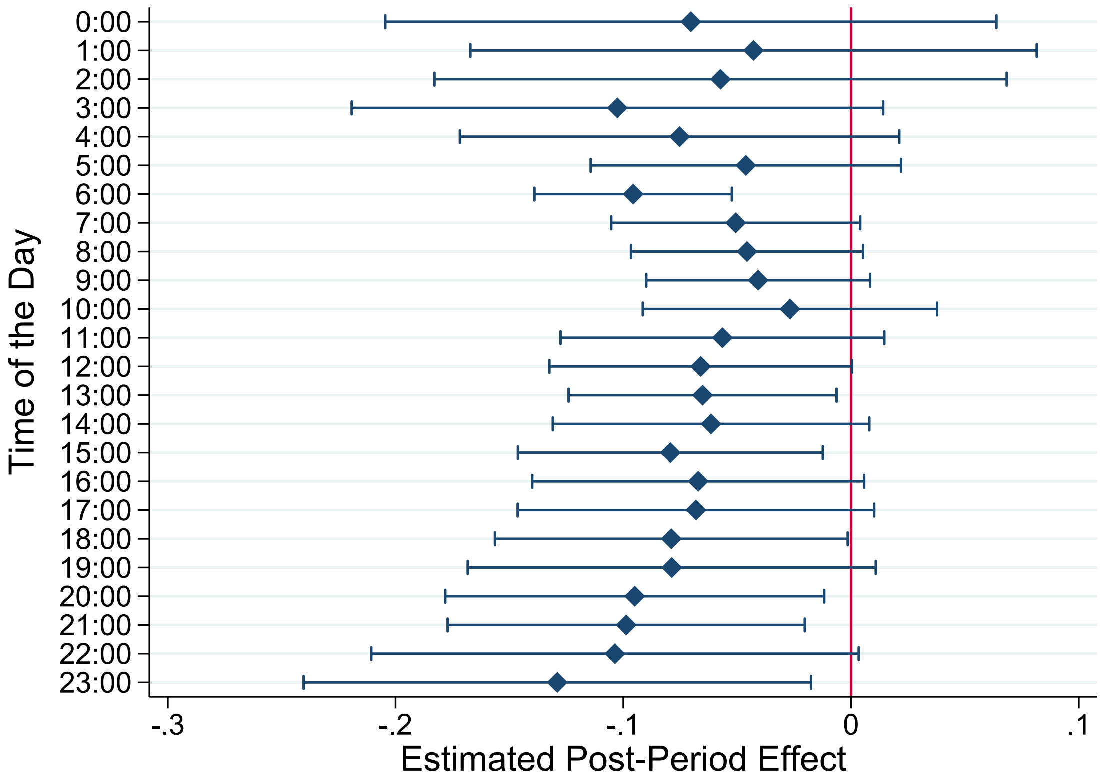


(d) Between 18:00 and 24:00



Notes: City-level event studies of the log number of pedestrians within a six-hour window in cities with an outbreak. The model controls for day times region fixed effects, city location times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Time $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The shaded area represents the seven-day period when the excess of cases is observed and information about the outbreak is revealed by the public health authorities.

Figure A12: Difference-in-Differences Estimates of the Behavioral Response to Outbreaks by Hour of the Day



Notes: This figure presents the difference-in-difference estimates of the event studies shown in Appendix Figure A11. The dependent variable is the log number of pedestrians passing by a city location in a city with an outbreak. The Post Period refers to $\Delta t \in (7, 21)$, where $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The estimates are normalized relative to the period $\Delta t \in (-21, -1)$. The model controls for day times region fixed effects, city-location times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Standard errors are clustered at the city level.

Table A9: Outbreaks identified by Ratio/Fixed Criteria

	Within	**Between**	$\log R_{ct}$
Post Period $\times$ Ratio Criterion (Eq. 2a)	-0.023**	-0.027***	-0.121***
	(0.007)	(0.007)	(0.021)
Post Period $\times$ Fixed Criterion (Eq. 2b)	-0.023***	-0.024***	-0.256***
	(0.005)	(0.006)	(0.038)
Observations	140350	140350	100359
Adj.R2.	0.994	0.992	0.164
FE	Yes	Yes	Yes

Notes: This table compares the behavioral response to different definitions of outbreaks relative to the base difference-in-difference estimates in Table 1. The dependent variables are the log number of trips taken within a county with an outbreak (Column 2), the log number of trips taken between the outbreak county and other counties (Column 3), and the log reproduction rate in a county $R_{ct} = \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Column 4). The first row captures the response to outbreaks identified by the Ratio Criterion (Equation 2a) and the second row captures the response to outbreaks identified by the Fixed Criterion (Equation 2b). The Post Period refers to $\Delta t \in (7, 21)$, where $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The estimates are normalized relative to the period $\Delta t \in (-21, -1)$. The estimates for the "Public Information" period $\Delta t \in (0, 6)$ and the corresponding interactions are not shown. The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Standard errors are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A10: Sensitivity Analysis: Description of Outbreaks

	Main Specification	**Change in Sum-Count Threshold**		**Change in X-Threshold**	
		28	**49**	**97^{th}**	**99^{th}**
1^{st} wave	105 (77, 28)	103 (74, 29)	98 (69, 29)	137 (104, 33)	61 (45, 16)
Summer	80 (36, 44)	98 (45, 53)	52 (23, 29)	101 (47, 54)	41 (15, 26)
2^{nd} wave	74 (48, 26)	72 (59, 13)	81 (56, 25)	115 (85, 30)	38 (23, 15)
Total	259 (161, 98)	273 (178, 95)	231 (148, 83)	353 (236, 117)	140 (83, 57)

Notes: The table summarizes the number of outbreaks per phase of the pandemic. The first number in the bracket refers to the number identified by Equation 2a and the second is identified by Equation 2b, respectively.

Table A11: Sensitivity Analysis: Changing the X-Threshold

	97^{th} Percentile			**98^{th} Percentile**			**99^{th} Percentile**		
	Within	**Between**	$\log R_{ct}$	**Within**	**Between**	$\log R_{ct}$	**Within**	**Between**	$\log R_{ct}$
Post Period	-0.0208***	-0.0233***	-0.1593***	-0.0234***	-0.0261***	-0.1711***	-0.0290***	-0.0364***	-0.1669***
	(0.004)	(0.004)	(0.017)	(0.005)	(0.005)	(0.021)	(0.008)	(0.008)	(0.033)
Observations	140350	140350	100358	140350	140350	100359	140350	140350	100359
Adj.R2.	0.994	0.992	0.163	0.994	0.992	0.164	0.994	0.991	0.158
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table compares the behavioral response using different definitions of outbreaks relative to the base difference-in-difference estimates in Table 1. Columns 2-4 (5-7) present results defining the X-threshold by the 97^{th} (99^{th}) percentile (*i.e.* X-Threshold), where the default is the 98^{th} percentile. The dependent variables are the log number of trips taken within a county with an outbreak (Column 2), the log number of trips taken between the outbreak county and other counties (Column 3), and the log reproduction rate in a county $R_{ct} = \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Column 4). The Post Period refers to $\Delta t \in (7, 21)$, where $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The estimates are normalized relative to the period $\Delta t \in (-21, -1)$. The estimates for the "Public Information" period $\Delta t \in (0, 6)$ and the corresponding interactions are not shown. The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A12: Sensitivity Analysis: Changing the Small-Count Threshold

	$\sum_{j=0,6} \hat{I}_{c,t+j} \lesseqgtr 28$			$\sum_{j=0,6} \hat{I}_{c,t+j} \lesseqgtr 35$			$\sum_{j=0,6} \hat{I}_{c,t+j} \lesseqgtr 49$		
	Within	**Between**	$\log R_{ct}$	**Within**	**Between**	$\log R_{ct}$	**Within**	**Between**	$\log R_{ct}$
Post Period	-0.0183***	-0.0224***	-0.1699***	-0.0234***	-0.0261***	-0.1711***	-0.0197***	-0.0245***	-0.1551***
	(0.005)	(0.005)	(0.022)	(0.005)	(0.005)	(0.021)	(0.006)	(0.005)	(0.021)
Observations	140350	140350	100359	140350	140350	100359	140350	140350	100359
Adj.R2.	0.994	0.992	0.167	0.994	0.992	0.187	0.994	0.991	0.158
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table compares the behavioral response using different definitions of outbreaks relative to the base difference-in-difference estimates in Table 1. Columns 2-4 (5-7) summarize results when changing the decision rule such that the expected number of cases must be below 28 (49) within a week (*i.e.* Small-Count Threshold), where the default threshold is 35 expected cases per week. The dependent variables are the log number of trips taken within a county with an outbreak (Column 2), the log number of trips taken between the outbreak county and other counties (Column 3), and the log reproduction rate in a county $R_{ct} = \sum_{\tau=t-6}^{\tau=t} I_{c,\tau} \Big/ \sum_{\tau=t-10}^{\tau=t-4} I_{c,\tau}$ (Column 4). The Post Period refers to $\Delta t \in (7, 21)$, where $\Delta t = 0$ is the first day of excess cases in the outbreak (see Section 4.2). The estimates are normalized relative to the period $\Delta t \in (-21, -1)$. The estimates for the "Public Information" period $\Delta t \in (0, 6)$ and the corresponding interactions are not shown. The model controls for day times state fixed effects, county times day-of-the-week fixed effects, and NPI indicators at the county-day level (see Section 4.3). Standard errors are clustered at the county level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$