

Kovacs, Roxanne; Dunaïski, Maurice; Tukiainen, Janne

Working Paper

Compulsory face mask policies do not affect community mobility in Germany

Suggested Citation: Kovacs, Roxanne; Dunaïski, Maurice; Tukiainen, Janne (2020) : Compulsory face mask policies do not affect community mobility in Germany, ZBW – Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/218945>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Compulsory face mask policies do not affect community mobility in Germany

Roxanne Kovacs* Maurice Dunaïski[†] Janne Tukiainen[‡]

June 5, 2020

Abstract

There is currently a heated debate about whether to introduce policies requiring the general public to wear protective face masks to contain COVID-19. A key concern is that compulsory face mask policies will make the public feel safer (due to risk compensation), and may consequently undermine the most important public-health advice to contain COVID-19 – which is to reduce mobility and maintain social distancing. This study provides first evidence on the impact of compulsory face mask policies on community mobility. We use a difference-in-differences design, which exploits the staggered implementation of compulsory face mask policies by German states. We use anonymised GPS data from Google’s Location History feature to measure daily mobility in public spaces (groceries and pharmacies, transport hubs and workplaces). We find no evidence that compulsory face mask policies affect community mobility in public spaces in Germany. The evidence provided in this paper makes a crucial contribution to ongoing debates about how to best manage the COVID-19 pandemic.

Keywords: COVID-19, face masks, social distancing, community mobility

JEL Codes: D9, H12, I12, I18

*London School of Hygiene & Tropical Medicine, Department of Global Health and Development, Keppel St, Bloomsbury, London WC1E 7HT, United Kingdom. email: roxanne.kovacs@lshtm.ac.uk

[†]London School of Economics & Political Science, Department of Government, Houghton St, Holborn, London WC2A 2AE, United Kingdom. email: m.r.dunaïski@lse.ac.uk

[‡]Department of Economics, Turku School of Economics, Rehtorinpellonkatu 3, FI-20014 University of Turku; VATT Institute for Economic Research, Arkadiankatu 7, Helsinki FI-00101. email: janne.tukiainen@utu.fi

1 Introduction

The ongoing coronavirus disease (COVID-19) pandemic has, as of June 2020, led to the death of over 380,000 people [WHO, 2020] and is expected to trigger a severe economic crisis, with global GDP growth predicted to fall to -3% [IMF, 2020]. One of the main ways in which governments have attempted to contain the spread of COVID-19 is through non-pharmaceutical interventions targeting citizens' behaviour. Policies that aim to curtail the spread of COVID-19 centre around reducing citizens' mobility and social contacts in order to disrupt the chain of transmission. Examples include closing schools, banning public gatherings, social distancing rules or lock-downs forbidding individuals to leave their homes [Mellan et al., 2020].

There is currently a heated debate about whether the general public should be required to wear protective face masks to further reduce the spread of COVID-19. For instance, the World Health Organization¹ advocates against the use of face masks by the general public, whilst the US Centres for Disease Control² advise the opposite. Nonetheless, over 50 countries already require the wearing of face masks in public spaces.³ Those arguing against introducing compulsory face mask policies frequently point to limited evidence on effectiveness, concerns about individuals wearing masks incorrectly, as well as high demand on masks reducing availability for healthcare workers [Feng et al., 2020, Greenhalgh et al., 2020]. Another key argument against making face masks compulsory, which motivates this paper, is the concern that individuals will feel safer and might therefore disregard the most important public-health advice to contain the spread of COVID-19 – which is to reduce mobility and maintain social distancing [Greenhalgh et al., 2020].

¹<https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/when-and-how-to-use-masks>

²<https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/diy-cloth-face-coverings.html>

³<https://www.aljazeera.com/news/2020/04/countries-wearing-face-masks-compulsory-200423094510867.html>

The effect of compulsory face mask policies on citizen’s mobility is *a priori* ambiguous. In line with concerns of policymakers,⁴ face masks could increase mobility due to risk compensation. A large economics literature examines behavioural responses to changes in perceived or actual risk [Peltzman, 1976]. Whilst the findings are mixed overall [Godlonton et al., 2016], a number of studies find evidence for risk-compensating behaviour, for instance, more risky sexual behaviour among recipient of the HPV vaccine [Kapoor, 2008], car accidents as a result of seat belt laws [Miller and Blomquist, 1989] and bicycle helmets triggering dangerous driving by cars [Walker, 2007]. Risk compensating behaviour is therefore a plausible mechanism through which protective technologies such as face masks, that reduce personal risk (whether actual or perceived), could lead to an increase in mobility.

In contrast, salience and what we refer to as the “hassle factor” provide reasons to expect that compulsory face mask policies reduce mobility. Face masks differ from previously studied risk-reducing technologies as they need to be worn constantly (unlike one-off treatments such as vaccines). Face masks might therefore serve as a constant reminder to citizens that the COVID-19 pandemic is ongoing and serious. It is therefore possible that compulsory face masks increase the salience of the COVID-19 pandemic in individuals’ decision making about their mobility [Van Der Pligt and De Vries, 1998]. Availability bias (where individuals judge events that come to mind more easily to be more likely) potentially exacerbates such an effect. For instance, studies have found that frequent exposure to drug advertisement influences individuals’ perceptions about disease prevalence [An, 2008]. Face masks might similarly inflate perceptions about the true prevalence of COVID-19 – which could affect mobility decisions about whether to visit any public space (i.e. not only locations where face masks are required by law). Another way in which face masks differ from previously studied risk-reducing technologies is that that they are bothersome to use (much more so than, for instance, seat belts). Wearing a face mask creates disutility, as wearers suggest

⁴see e.g. <https://www.theguardian.com/uk-news/2020/jun/04/do-face-coverings-reduce-risk-and-spread-of-coronavirus?> and <https://www.theguardian.com/commentisfree/2020/apr/24/face-masks-mandatory-spread-coronavirus-government>

that masks can be hot, uncomfortable, humid, itchy and odorous [Li et al., 2005]. This disutility, which we refer to as the “hassle factor”, can spoil the fun of non-essential outings and could incentivise individuals to minimise the frequency of essential outings – which could reduce mobility. Due to the extensively studied process of adaptation, through which one quickly adjusts to new or changed circumstances, we expect that any such effects should be short-lived [Dolan and Kahneman, 2008]. In addition, as the hassle factor only comes into play when masks are worn, it should primarily affect mobility in locations where face masks are required by law.⁵

This study provides first evidence on the effect of compulsory face mask policies on community mobility. To isolate the causal effect of such policies, we use a difference-in-differences design, which exploits the staggered introduction of policies requiring the wearing of face masks in shops and public transport by German states (Bundesländer). Saxony was the first state to introduce compulsory face masks on the 20th of April 2020, Schleswig-Holstein was the last to do so on the 29th of April 2020.⁶ To measure community mobility, we rely on the Google COVID-19 Community Mobility Reports, which use GPS data from Google’s Location History users to provide anonymised and aggregated (state-level) measures of the number of hours spent at home as well as the number of times public spaces are visited each day. Community mobility has been previously measured in this way in epidemiological studies [Mellan et al., 2020] to estimate the basic reproduction number R_0 , which is a key parameter of transmission intensity and therefore highly relevant for containing the spread of COVID-19.

We measure community mobility within each German state between March 23rd and May 21st 2020. Our main outcome is an aggregate measure of mobility in public spaces, which captures

⁵In a setting where face masks are voluntary, an additional reason why masks could reduce mobility is that individuals perceive masks as a signal for a larger preferred social distance by the wearer, as found by Seres et al. [2020]

⁶All states except Berlin introduced compulsory face masks in shops and public transport on the same date. In Berlin, masks became compulsory in public transport on April 27th and in shops on April 29th.

visits to grocery and pharmacy shops, workplaces and transport hubs. We also measure the number of hours spent in places of residence as well as mobility patterns in specific locations. We focus on an aggregate measure of mobility in public spaces, as policymakers are likely most interested in changes in overall mobility patterns, rather than changes in mobility for specific locations (for instance, only grocery shops).

We do not find evidence to suggest that compulsory face mask policies affect community mobility in public spaces in Germany. Effect sizes are precisely estimated and we can rule out even small increases in mobility that are larger than 0.03 SD. We only find a small reduction in average community mobility on the day of the policy change (-0.14 SD), but find no longer-term effects thereafter. We also find no evidence suggesting that, beyond a short-term increase during the first four days, compulsory face mask policies affect the number of hours spent at home, which is another “catch-all” measure of community mobility. We take this to suggest that these policies are complementary to interventions aimed at reducing mobility and disrupting the chain of transmission of COVID-19. When we examine mobility in specific locations, we find that mobility patterns are lower in grocery shops and pharmacies for five days following the introduction of compulsory face masks, but that the magnitude of the reduction is modest. We find no effects on mobility patterns in workplaces or transport hubs (subways, buses or train stations).

This paper makes three main contributions. First, it provides new evidence that is crucial to ongoing policy debates on how to best manage the COVID-19 pandemic. Policymakers and researchers have expressed concerns that making face masks compulsory could lead people to disregard measures that are key for containing COVID-19. We are unable to provide evidence on important individual-level behaviours such as hand-washing or social distancing. However, community mobility plays a key role in reducing the spread of COVID-19 [Mellan et al., 2020] and we find no evidence to suggest that, in Germany, compulsory face mask policies led to an increase in mobility. If anything, we observe a temporary decrease in

mobility in grocery shops and pharmacies. This is important information for policy-makers considering the costs and benefits of compulsory face mask policies, as such analysis likely do not have to account for spillovers on mobility.

Second, we contribute to the small but rapidly growing literature using aggregate GPS data to study the effect of policies trying to contain the spread of COVID-19 on mobility patterns [Allcott et al., 2020, Wellenius et al., 2020, Dasgupta et al., 2020]. Using GPS data is one of the main alternatives to using surveys [Briscese et al., 2020, Jørgensen et al., 2020], which likely do not provide reliable data on mobility due to social desirability bias [Daoust et al., 2020].

Finally, our findings speak to the behavioural economics literature on risk compensation [Godlonton et al., 2016, Peltzman, 1976, Kapoor, 2008, Miller and Blomquist, 1989, Walker, 2007]. To our knowledge, only one previous study has examined the effect of face masks on risk compensating behaviour, finding that physical distancing increases by on average 9cm when individuals wear masks - supposedly because others interpret face masks as a signal for a larger preferred distance [Seres et al., 2020]. This paper complements the study by Seres et al. [2020] by providing evidence from a large sample. This study is also the first to investigate the general equilibrium effect of introducing compulsory face masks - where signalling is unlikely to play a role. We show that even though compulsory face mask policies may reduce personal risk and risk imposed on others, there is no evidence of an undesirable aggregate effect on community mobility.

2 Background

Germany is frequently put forward as a positive example for how to manage the COVID-19 pandemic.⁷ As of June 5th 2020, there have been 183,271 confirmed cases of COVID-19 in Germany and 8,613 deaths [RKI, 2020]. There are arguably two main reasons for Germany’s relative success in handling the COVID-19 pandemic. First, Germany started testing early and it tested a broad sample of the population. This stands in contrast to some other European countries, which focused on testing elderly populations or those in critical care [Stafford, 2020]. Due to its federal healthcare system, Germany also does not face testing constraints created by having only a few central laboratories, as is the case in many other countries [Stafford, 2020]. Second, containment measures to reduce the population’s mobility (e.g. closing schools, retail businesses and banning public gatherings), and to thereby break the chain of transmission, began comparatively earlier than in other countries [Stafford, 2020].

Germany’s 16 states introduced compulsory face mask policies at different times in late April 2020.⁸ Saxony was the first state, on the April 20th 2020, followed by Saxony-Anhalt on April 23th and Thuringia on April 24th. Twelve states adopted compulsory face mask policies on April 27th, and Schleswig-Holstein followed suit on April 29th. All states except Berlin made face masks compulsory in public transport as well as in shops at the same time. In Berlin, face masks first became compulsory in public transport (April 27th) and in shops two days later. As of June 5th, compulsory face mask policies remain in place in all German states, although some state governments have expressed a desire to abolish the requirement.⁹ In

⁷e.g. <https://www.theguardian.com/world/2020/may/21/covid-19-track-and-trace-what-can-uk-learn-from-countries-got-it-right>

⁸In all states, the face mask requirement is fulfilled by wearing a non-surgical mask, bandana or scarf that covers one’s mouth and nose (called Mund-Nasen-Bedeckung). Children under the age of six and people with disabilities are usually excluded from the face mask requirement.

⁹see <https://www.theguardian.com/world/2020/may/25/german-state-causes-alarm-with-plans-to-ease-lockdown-measures-thuringia-second-wave-coronavirus> and <https://www.zeit.de/politik/deutschland/2020-05/thueringen-kontaktverbot-corona-verordnung-lockerung>

Appendix A we provide a complete overview of the staggered introduction of compulsory face mask policies in Germany. We also record when other policies related to COVID-19 (e.g. school or retail re-openings) were implemented, given that these policies may have also affected community mobility in the study period.¹⁰

Even though compulsory face mask policies make it illegal not to wear a mask in designated spaces, only nine out of 16 states introduced fines for not wearing masks.¹¹ Overall, the German approach “seems to be characterised more by appealing on compliance to rules rather than on enforcing them by micromanagement law” [Stafford, 2020]. Although data on compliance with compulsory face mask policies are, to our knowledge, currently not available, these policies appear to be widely supported by the German public. Nationally representative survey evidence suggests that, before the first state-wide introduction in late April 2020, compulsory face mask policies were supported by more than 85% of the population¹². More than one month into the nation-wide face mask requirement, support remains high at around 80%.¹³

Several factors could explain why some states implemented compulsory face mask policies earlier than others. First, one could see the staggered introduction as being due to a process of bottom-up policy diffusion. For example, Thuringia implemented a state-wide compulsory face mask policy around two weeks after its second-largest city, Jena, became the first city in Germany to require face masks in public spaces.¹⁴ The federal government largely took a back seat and continued to recommend voluntary face mask use, even as several states had already

¹⁰In some instances, these additional policy changes coincided with the introduction of compulsory face mask policies. We discuss the implications for our identification strategy in Section 3.

¹¹Fines of varying amounts are in place in Baden-Wuerttemberg, Bavaria, Berlin, Hamburg, Hesse, Lower Saxony, Mecklenburg-West Pomerania, North Rhine-Westphalia and Rhineland-Palatinate. In some cases (e.g. NRW), fines vary within the state and are enforced at the discretion of local councils.

¹²BfR Corona Monitor, 26 May 2020: <https://www.bfr.bund.de/cm/349/200526-bfr-corona-monitor-en.pdf>

¹³BfR Corona Monitor, 26 May 2020: <https://www.bfr.bund.de/cm/349/200526-bfr-corona-monitor-en.pdf>

¹⁴In Jena, the local health authority had recommended compulsory face masks (see <https://www.spiegel.de/panorama/gesellschaft/die-stadt-der-schoenen-muster-a-7a65406c-6b4e-4e8f-8734-483942e59d5d>)

introduced compulsory measures.¹⁵ A second interpretation is that variation in the supply of face masks and concerns about compulsory face masks leading to panic-buying played a role. For example, the governments of Bavaria, Lower Saxony and North Rhine-Westphalia initially resisted moves to introduce compulsory face masks on these grounds.¹⁶ Third, geographic variation in transmission rates could have prompted some cities (and states) to move earlier than others. For example, Jena was considered a COVID-19 “hotspot” before it introduced compulsory face masks.¹⁷

Even though some evidence from the USA suggests that party ideology is associated with support for face masks,¹⁸ this does not appear to be the case in Germany. For instance, Jena is governed by the liberal *FDP*. The first state to implement compulsory face masks (Saxony) is governed by the centre-right *CDU*, while another early mover (Thuringia) is governed by the left-wing *Die Linke*.

3 Data and methods

3.1 Data

To measure community mobility, we use the publicly available Google’s COVID-19 Community Mobility Reports for Germany.¹⁹ These data capture daily changes in mobility patterns in each German state based on GPS data from Google Account users who have opted-in to

¹⁵<https://www.bundesregierung.de/breg-de/themen/coronavirus/empfehlung-schutzmasken-1745224>

¹⁶<https://www.dw.com/de/streit-über-maskenpflicht-gegen-die-corona-pandemie-entbrannt/a-52969231>, [kurier.de/inhalt/corona-massnahmen-spd-ministerpraesident-erwartet-baldige-maskenpflicht.84385fb6-ca08-4226-9601-0336a812919d.html](https://www.kurier.de/inhalt/corona-massnahmen-spd-ministerpraesident-erwartet-baldige-maskenpflicht.84385fb6-ca08-4226-9601-0336a812919d.html), and <https://www.aachener-zeitung.de/nrw-region/spahn-und-laschet-gegen-maskenpflicht-in-deutschland-aid-49847769>

¹⁷<https://www.mdr.de/thueringen/ost-thueringen/jena/corona-jena-seit-einer-woche-keine-neuinfektion-100.html>

¹⁸<https://tompepinsky.com/2020/05/13/yes-wearing-a-mask-is-partisan-now/>

¹⁹Data are updated regularly (roughly once a week) and available at: <https://www.google.com/covid19/mobility/>

the Location History feature. We use mobility data from the period between March 23rd and May 21st. We exclude observations from before the national lock-down (i.e. before March 23rd), as mobility reduced drastically in the preceding days, which could distort our estimates (see Figure 1 below).

Google’s COVID-19 Community Mobility Reports are disaggregated by place categories. The data capture the number of visits to groceries and pharmacies (grocery markets and food shops, food warehouses, farmers markets, drug stores, and pharmacies), transit stations (transportation hubs including subway, bus, and train stations), parks (local and national parks, beaches, marinas, public gardens) and retail and recreation (restaurants, cafes, theme parks, shopping centres, museums, libraries and cinemas) [Aktay et al., 2020]. The data also capture mobility patterns for places of work and residence. For workplaces, Google uses the relative frequency of visits, as well as time and duration to calculate how many individuals spent more than one hour at their place of work [Aktay et al., 2020]. A similar process is used to calculate the number of hours spent in places of residence [Aktay et al., 2020].

For each day, the data record the percentage change in the number of visits (or length of stay) relative to a baseline value for that day of the week. This baseline is the median value for the corresponding day of the week in the five-week period between January 3rd and February 6th 2020.²⁰ This process is similar the one used to create “popular times” for places in Google Maps. Observations that do not meet Google’s required privacy thresholds are coded as missing by Google.²¹ Importantly, these data are based on Google Account users who opted-in to the Location History feature. This means that the data are not necessarily representative of the German population.

²⁰This means there are 7 x 16 baseline values, one for each state and day of the week. Google does not provide data on the baseline total count/number (visits, hours spent), but only percentage changes relative to the (unknown) baseline. We address this issue by including state * day-of-the-week fixed effects in our model specification (see Section 3.3)

²¹In our study period, this only pertains to mobility data for groceries and pharmacies on three Sundays in Berlin

We focus on mobility in public spaces, captured by the percentage change in the number of visits to (or time spent in) groceries and pharmacies (GP), workplaces (W) and transit stations (T). The main outcome of interest is the percentage change in average community mobility in public spaces, equal to $\frac{GP+W+T}{3}$, relative to the baseline. We also use the percentage change in the number of hours spent at home relative to the baseline as an additional catch-all measure. For the sake of simplicity, we use the terms “mobility patterns” or “mobility”, to refer to percentage change in the number of visits to (or time spent in) public spaces or number of hours spent at home.

We would like to highlight that the Google data can be used to measure community mobility patterns, but do not provide a good measure of social distancing, as implied in several recent studies [Wellenius et al., 2020, Schrimpf et al., 2020, Ansell, 2020]. The term “social distancing” refers to the physical (Euclidean) distance between two people,²² which is not directly captured by the Google mobility data. Even though it is plausible that once mobility (i.e. number of visits to public spaces) reaches a certain level, social distancing will be harder to maintain in some locations, it is unclear how this can be accurately inferred from the data.

Google also provides mobility data on parks as well as retail and recreation. However, these locations are less relevant for our analysis. This is because some places that fall within the park category are arguably not relevant for the spread of COVID-19 (for instance national parks, where the risk of transmission is likely extremely low). We also do not consider retail and recreation, given that for most of the study period, the places that fall into this category (e.g. restaurants, cafes or cinemas) were required to close.

To create a timeline for when German states introduced compulsory face mask policies, we consulted state-specific secondary legislation (Verordnungen), which are typically published on states’ official websites. We also extracted information from the German Catalogue of

²²US Centres for Disease Control: <https://www.cdc.gov/coronavirus/2019-ncov/prevent-getting-sick/social-distancing.html>

Fines (“Bußgeldkatalog”), which records penalties for not wearing face masks in different states,²³, as well as from official announcements made to national and local newspapers. Through the same process, we identified when states implemented other important policies related to the COVID-19 pandemic that could also affect community mobility patterns. We systematically extracted information on the re-opening of schools and shops, as well as the official start and end of state-specific stay-at-home orders (“Ausgangsbeschränkungen”).

Finally, we obtain the daily number of new confirmed COVID-19 cases in each state from the Robert Koch Institute (RKI), which is the German federal government agency responsible for disease control and prevention.²⁴ We use RKI data for the period between March 23rd and May 21st.

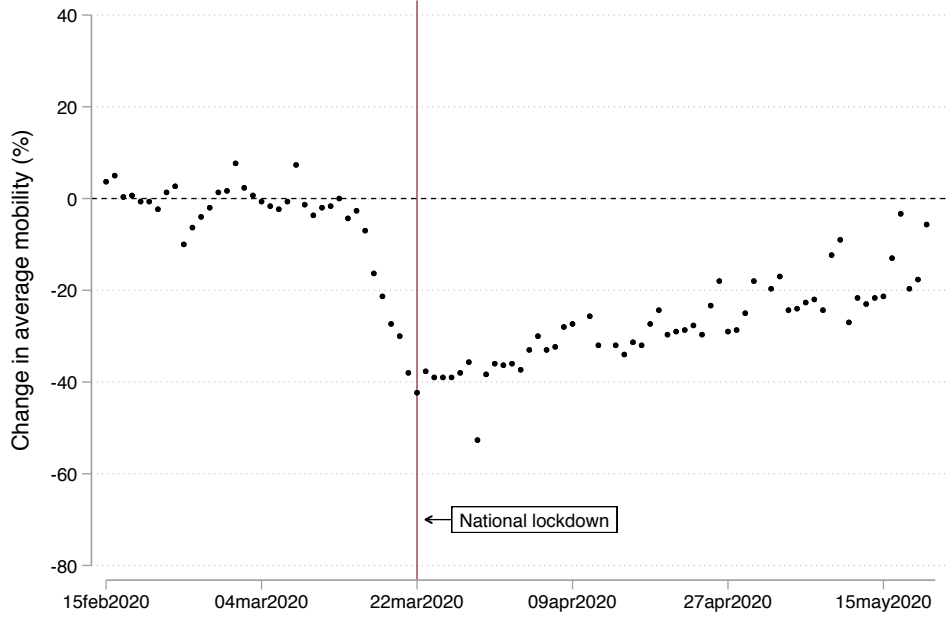
3.2 Mobility trends

Figure 1 provides a descriptive overview of changes in average mobility in public spaces (groceries and pharmacies, workplaces and transit stations). It shows that mobility in public spaces in Germany decreased substantially in the period leading up to the national-level lock-down on March 23rd 2020. As shown in Appendix B, similar patterns can be observed for mobility trends in specific public spaces (separately for groceries and pharmacies, workplaces and transit station). The number of hours spent in places of residence increased over the same time period, although changes appear less drastic, as individuals already spend a large proportion of their time at home (see Appendix B).

²³<https://www.bussgeldkatalog.org/corona/>

²⁴<https://npgeo-corona-npgeo-de.hub.arcgis.com/>

Figure 1: Average mobility in public spaces in Germany



Note: This graph shows the percentage change in average mobility in public spaces (groceries and pharmacies, workplaces, and transit stations) for each day between Feb 15th and May 21st 2020 relative to the baseline. The baseline is the median value for the corresponding day of the week in the five-week period between Jan 3rd and Feb 6th 2020. *Data:* Google COVID-19 Community Mobility Reports.

3.3 Methods

To isolate the causal effect of compulsory face mask policies, we use a generalised difference-in-differences (DD) design that exploits the staggered introduction of compulsory face mask policies in German states. In this setup, all units are eventually “treated” (i.e. all states implement a compulsory face mask policy), but at different times.

We first use a static DD model:

$$Y_{st} = \alpha_s + \beta_t + \gamma D_{st} + X'_{st} + \eta_0 + \epsilon_{st} \quad (1)$$

where Y_{st} is a measure of community mobility, D_{st} is a treatment indicator equal to one for

states and dates where compulsory face mask policies are in place and zero otherwise,²⁵ α_s denotes state-level fixed effects, β_t denotes date fixed effects, and X'_{st} is a vector of time-varying state-specific controls,²⁶ η_0 is a constant, and ϵ_{st} is an error term. The coefficient of interest is γ , which identifies the effect of compulsory mask policies on community mobility under the parallel trends assumption.²⁷

Given that the static DD estimates can be biased when treatment effects vary over time [Goodman-Bacon], we use an event study approach that allows us to examine the effect of the policy for the days before and after implementation. In the main event study specification, the data are trimmed so that the panel is balanced in time periods (days) relative to the treatment, as recommended by Abraham and Sun [2018]. Our “trimmed” panel contains 22 days before and 22 days after the treatment date in each state.²⁸

To investigate pre-trends, we use a “fully dynamic” event study model, which is specified as follows:

$$Y_{st} = \alpha_s + \beta_t + \sum_{\ell=-21}^{-2} \gamma_{\ell} D_{st}^{\ell} + \sum_{\ell=0}^{22} \gamma_{\ell} D_{st}^{\ell} + X'_{st} + \epsilon_{st} \quad (2)$$

where $D_{st}^{\ell} = \mathbf{1}\{t - E_s = \ell\}$ is a “switch-on switch-off” indicator for unit s being periods ℓ away from the initial treatment period E_s at calendar time t . In the trimmed specification,

²⁵For Berlin, we code $D_{st}=1$ following the introduction of compulsory face masks in public transport on April 27th. The policy was extended to shops two days later.

²⁶The controls are an indicator for state-specific public holidays (Tag des Sieges in Berlin), an indicator for when states relaxed their stay-at-home orders (Ausgangsbeschränkungen), the daily new confirmed COVID-19 cases in each state (lagged by one day), an indicator for when states re-opened secondary schools for final year classes, an indicator for when states allowed retail shops $< 800 \text{ m}^2$ to re-open, an indicator for when states allowed retail shops to re-open without any size restrictions, and state*day-of-the-week fixed effects.

²⁷The parallel trends assumption is that community mobility trends in treated and untreated states would have developed in parallel in the absence of the compulsory face mask policies. We assess the plausibility of this assumption by inspecting pre-treatment trends in a “fully dynamic” event study framework (see below)

²⁸Schleswig-Holstein is the last state to receive treatment on April 29th. A panel that is balanced in periods relative to the treatment can contain at most 22 treatment leads and 22 treatment lags, given that the Google mobility data available up until May 21st.

distant relative periods (where $|\ell| > 22$) are excluded so that the panel is balanced in periods relative to the treatment. Furthermore, the first and last treatment lead are set to zero to address under-identification in the fully dynamic model [Borusyak and Jaravel, 2017].

To assess how treatment effects change over time, we instead use a "semi-dynamic" event study model, where all leads are set to zero. This specification is robust to event-time treatment effect heterogeneity, so it is more likely to provide unbiased estimates of how the face mask policy affects mobility patterns over time. The semi-dynamic model is specified as follows:

$$Y_{st} = \alpha_s + \beta_t + \sum_{\ell=0}^{22} \gamma_{\ell} D_{st}^{\ell} + X'_{st} + \epsilon_{st} \quad (3)$$

All models are estimated using OLS with robust standard errors clustered at the state level. We also use a wild cluster bootstrap procedure to obtain more accurate p-values [Roodman et al., 2019]. This is advisable given that in a setting with few clusters (16 states) the standard cluster-robust variance estimator may lead to over-rejection of the null and confidence intervals that are too narrow [Bertrand et al., 2004, Cameron et al., 2008]. We report bootstrapped p-values in the main results table and refer to Appendix F.3 for more details on the bootstrap procedure.

4 Results

4.1 Effect of compulsory face masks on mobility in public spaces

We first present results from our static DD specification (Equation 1) which investigates the average effect of introducing compulsory face mask policies on community mobility. As shown in Table 1, we do not find evidence to suggest that compulsory face mask policies affect average mobility in public spaces. Overall, the estimated effects are not statistically significant and relatively small in magnitude, lying between -0.8 percentage points (-0.05 SD) and -1.8 percentage points (-0.11 SD). Column 5 shows results for our preferred model specification, which includes state and date fixed effects and a broad range of state-specific controls: public holidays, the daily number of new COVID-19 cases in each state (lagged by one day), and several policy changes that are likely to affect community mobility (lock-down rules being relaxed, secondary schools and retail re-opening). The main treatment effect is quite precisely estimated and we can rule out even small increases in mobility that are larger than 0.03 SD.

Column 6 shows results for a more flexible model, which also includes an interaction between day-of-the-week and state fixed effects. In contrast to all other models, the model suggests a significant negative effect of -1.8. Our sense is that this is because this static model heavily weighs changes occurring shortly after the treatment - an issue we examine further in the next section.

Table 1: Effect of compulsory face mask policies on mobility in public spaces

	(1)	(2)	(3)	(4)	(5)	(6)
Face mask policy	-0.759 (0.703) [0.333]	-1.075 (0.692) [0.211]	-1.074 (0.700) [0.214]	-1.591 (0.946) [0.199]	-1.500 (0.924) [0.210]	-1.763** (0.605) [0.027]
State FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-specific holidays		✓	✓	✓	✓	✓
Lockdown relaxed		✓	✓	✓	✓	✓
COVID-19 cases (t-1)			✓	✓	✓	✓
Sec. school open				✓	✓	✓
Retail open					✓	✓
State * Day-of-week FE						✓
Observations	960	960	960	960	960	960
R-squared	0.965	0.973	0.973	0.973	0.973	0.985
Clusters	16	16	16	16	16	16

Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Wild cluster (state-level) bootstrap p-values in square brackets.

Outcome mean -30.19 and SD 16.94.

Appendix C shows results for specific public spaces. We find that the introduction of compulsory face masks leads to a small but statistically significant reduction in mobility for visits to grocery stores and pharmacies of -4.9 percentage points or -0.4 SD (95% CI between -0.28 and -0.10). We also find evidence for a small increase in the number of hours spent at home of 0.08 SD (95% CI between 0.03 SD and 0.13 SD). Our static models do not detect significant effects on mobility in workplaces and transit stations.

4.2 Dynamic effects

Next, we use event study models to assess parallel trends and examine how compulsory face masks affect mobility patterns over time.²⁹ In Appendix D, we present results from the fully dynamic specification (Equation 2), which allows us to assess the parallel trends assumption. The absence of apparent pre-treatment trends suggests that our identification strategy is valid.

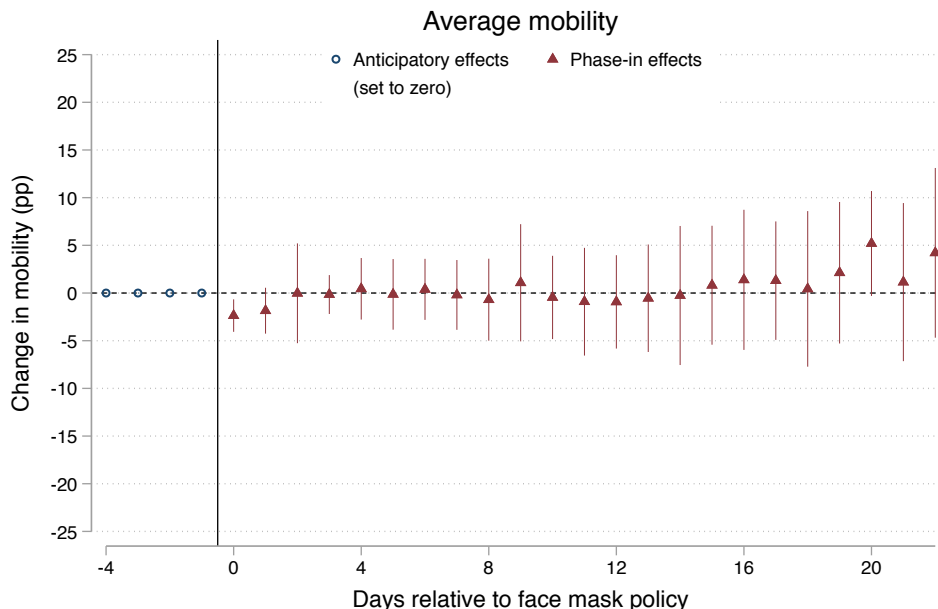
We use the semi-dynamic specification (Equation 3) to investigate potential over-time effects of compulsory face mask policies. Figure 2 below summarises the results from the semi-dynamic model. We do not find evidence to suggest that compulsory face mask policies affect mobility in public spaces over time. There is a significant decrease in mobility the day compulsory face mask policies are introduced. This decrease is equal to -2.4 percentage points or -0.14 SD (95% CI between -0.24 and -0.04), which is small in magnitude and comparable to the static DD estimate. We do not detect any significant effects on mobility for any other days following the policy change.

In Appendix E we examine over-time effects for mobility patterns in specific public spaces as well as time spent at home. We find that mobility in grocery shops and pharmacies decreases by between -7.7 percentage points (-0.31 SD) and -2.2 percentage points (-0.1 SD) within the first five days of the policy change, which is consistent with static DD estimates. This effect, however fades out over time. We find only sporadic evidence for a positive over-time effect on mobility in places of work (for instance, a 2.8 percentage point (0.15 SD) increase on the 3rd day following the change, and a 3.6 percentage point (0.19 SD) increase on the 4th day). However, point estimates are imprecise and rarely distinguishable from zero. In terms of hours spent at home, we find a small increase within the first four days (between 0.14

²⁹All event study models include controls from our preferred static DD model specification: state-specific public holidays, the daily number of new COVID-19 cases in each state (lagged by one day), and dummies for several policy changes that are likely to affect community mobility (lock-down rules being relaxed, secondary schools and retail re-opening).

and 0.17 SD). We find no significant effects on mobility patterns in transit hubs. Overall, our results suggest that compulsory face mask policies only affect mobility in the very short term, with no detectable medium-term effects.

Figure 2: Semi-dynamic event study estimates



Note: This graph shows the estimated over-time effect of compulsory face mask policies on average mobility in public spaces (groceries and pharmacies, workplaces, and transit stations) for 22 days after the policy change. Point estimates are obtained from a semi-dynamic event study model, where all treatment leads are set to zero and the panel is “trimmed” such that it is balanced in time periods (days) relative to the policy change. The model includes controls from our preferred static DD model specification: state-specific public holidays, the daily number of new COVID-19 cases in each state (lagged by one day), and dummies for several policy changes that are likely to affect community mobility (lock-down rules being relaxed, secondary schools and retail re-opening). Vertical lines represent cluster-robust 95% confidence intervals.

4.3 Robustness checks

We conduct a number of robustness checks. First, we run the fully-dynamic specification using a “binning” approach [Abraham and Sun, 2018], where we replace the first and last switch-on-switch-off leads and lags with switch-on-stay-on indicators (see Equation 4). As

shown in Appendix F.1, the main results hold using this alternative event study specification. Second, we address the potential problem of negative weighting in the static DD setup by using a control group of states that are never exposed to the treatment, but plausibly face the same time effects as the treatment group [Borusyak and Jaravel, 2017]. To this end, we drop all observations from April 27th onwards. The four states that made face masks compulsory before April 27th now constitute the treatment group and the remaining twelve states are part of the never-treated control group. As shown in Appendix F.2, we also do not find evidence that compulsory face masks affect community mobility using this alternative specification. Finally, we address the potential concern that our null-results are an artefact of too-few clusters [MacKinnon and Webb, 2018]. We show that the main results hold when using a “sub-cluster” wild bootstrap procedure (see Appendix F.3) and robust standard errors clustered at the state-week level (see Appendix F.4).

5 Discussion

There is an ongoing debate about whether to introduce policies requiring the general public to wear protective face masks. A key concern is that individuals could feel safer as a result and, due to risk compensating behaviour, increase their mobility. This could undermine the most important public-health advice to contain the spread of COVID-19 – which is to reduce mobility and maintain social distancing [Greenhalgh et al., 2020]. We provide first empirical evidence on the impact of compulsory face mask policies on community mobility. We do not find evidence to suggest that, in Germany, compulsory face mask policies affect mobility in public spaces (groceries and pharmacies, workplaces and transit hubs).

When examining mobility in specific locations, we find a short-lived reduction in the number of visits to groceries and pharmacies and a short-lived increase in the number of hours spent at home (respectively within five and four days of the policy change). We find no significant

over-time effects on mobility in workplaces and transit hubs. Our overall interpretation of the results is that compulsory face mask policies in Germany did not affect community mobility. We do not examine how compulsory face mask policies affect important individual behaviours such as hand-washing and social distancing. However, the findings presented here should to some degree alleviate policy makers' concerns about compulsory face mask policies leading to an increase in community mobility.

Even though compulsory face mask policies have been introduced in several countries, we currently lack systematic evidence on the effect of face masks on human behaviour. A recent small-scale field experiment implemented in Berlin before face mask became compulsory, finds that masks increase physical distancing by 9cm on average [Seres et al., 2020] - thereby providing no evidence of risk compensating behaviour. The authors hypothesise that this is due to others perceiving face masks as a signal of a larger preferred physical distance by the wearer. Even though this signalling effect most likely disappears in a setting where face masks are compulsory, we also do not find evidence for risk compensation at the community level.

There are two potential mechanisms which could explain our main finding that compulsory face mask policies have no discernible effect on community mobility. First, it might be that there is simply no risk compensating behaviour when it comes to face masks. Second, it might be that any risk compensation (which would increase mobility) is outweighed by increased salience or the hassle factor (which would decrease mobility). In terms of mobility in specific locations, we find a negative but short-lived effect on the number of visits to groceries and pharmacies - where face masks are required. Given that the effect occurs immediately and fades out very quickly, we believe that the hassle factor provides a better explanation than increased salience (where negative effects would arguably persist over time). This explanation has intuitive appeal. As face masks are uncomfortable to wear, individuals initially make fewer visits to locations where face masks have to be worn, until they adapt to

the new circumstances. One reason why we observe an effect for groceries and pharmacies but not for transit hubs could be that it is easier and less costly for individuals to change the frequency of visits to grocery shops, but that this is more difficult for transit. As we do not have access to individual-level data, we are unfortunately not in a position to test these hypotheses.

Our results are limited in three main respects. First, we are only able to observe the effect of compulsory face mask policies in the medium-term (up to three weeks after the policy change). It is possible that there are changes to community mobility in the long run that we are not able to detect. However, our results suggest that any changes in mobility fade out within days of the policy change and it is unclear if one would expect additional changes in behaviour after an initial adaptation. Second, one concern with the Google COVID-19 Community Mobility Reports is that the data are based on Google Account users who opted-in to Google’s Location History feature. It is therefore likely that these data are from a non-random sub-sample of the German population. Whilst we have no data on the number of people using this feature, Germany has a very high smartphone penetration. Over 98% of people under 50 years of age and 80% on average use a smartphone with Android as the main operating system.³⁰ An additional concern is that the accuracy and coverage of the data vary across sub-national units (e.g. between urban and rural areas) in a systematic manner that is associated with the timing of the policy change.

Finally, whilst this paper provides important evidence for current policy debates on how to manage the COVID-19 pandemic, it is unclear if results can be generalised to other settings. The Google mobility data used in this paper, or other sources of aggregate level GPS data, could be used to determine the effect of compulsory face mask policies in other countries. Further research is also needed on the impact of compulsory face mask policies on other important behaviours such as hand washing and social distancing.

³⁰<https://www.statista.com/statistics/469969/share-of-smartphone-users-in-germany-by-age-group/>

References

- Sarah Abraham and Liyang Sun. Estimating Dynamic Treatment Effects in Event Studies With Heterogeneous Treatment Effects. *SSRN Electronic Journal*, 2018. doi: 10.2139/ssrn.3158747. URL <https://arxiv.org/abs/1804.05785>.
- Ahmet Aktay, Shailesh Bavadekar, Gwen Cossoul, John Davis, Damien Desfontaines, Alex Fabrikant, Evgeniy Gabrilovich, Krishna Gadepalli, Bryant Gipson, Miguel Guevara, Chaitanya Kamath, Mansi Kansal, Ali Lange, Chinmoy Mandayam, Andrew Oplinger, Christopher Pluntke, Thomas Roessler, Arran Schlosberg, Tomer Shekel, Swapnil Vispute, Mia Vu, Gregory Wellenius, Brian Williams, and Royce J Wilson. Google COVID-19 Community Mobility Reports: Anonymization Process Description (version 1.0). apr 2020. URL <http://arxiv.org/abs/2004.04145>.
- Hunt Allcott, Levi Boxell, Jacob Conway, Matthew Gentzkow, Michael Thaler, and David Y. Yang. Polarization and Public Health: Partisan Differences in Social Distancing during COVID-19. *SSRN Electronic Journal*, 2020. ISSN 0898-2937. doi: 10.2139/ssrn.3570274. URL <https://www.nber.org/papers/w26946>.
- Soontae An. Antidepressant direct-to-consumer advertising and social perception of the prevalence of depression: Application of the availability heuristic. *Health Communication*, 23(6):499–505, nov 2008. ISSN 10410236. doi: 10.1080/10410230802342127.
- Joshua D. Angrist and Jörn-Steffen Pischke. *Mostly Harmless Econometrics*. 2009. doi: 10.2307/j.ctvc4j72. URL <https://press.princeton.edu/books/paperback/9780691120355/mostly-harmless-econometrics>.
- Ben Ansell. What explains differences in social distancing in the UK? (April):1–15, 2020. URL <https://ukandeu.ac.uk/research-papers/what-explains-differences-in-social-distancing-in-the-uk/>.
- M. Bertrand, E. Duflo, and S. Mullainathan. How Much Should We Trust Differences-In-Differences Estimates? *The Quarterly Journal of Economics*, 119(1):249–275, feb 2004. ISSN 0033-5533. doi: 10.1162/003355304772839588. URL <https://academic.oup.com/qje/article-lookup/doi/10.1162/003355304772839588>.
- K Borusyak and X Jaravel. Revisiting Event Study Designs. 2017. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2826228.
- Guglielmo Briscese, Nicola Lacetera, Mario Macis, and Mirco Tonin. Compliance with COVID-19 Social-Distancing Measures in Italy: The Role of Expectations and Duration. Technical report, National Bureau of Economic Research, Cambridge, MA, mar 2020. URL <http://www.nber.org/papers/w26916.pdf>.
- A. Cameron, Jonah B. Gelbach, and Douglas L. Miller. Bootstrap-based improvements for inference with clustered errors. *Review of Economics and Statistics*, 90(3):414–427, aug 2008. ISSN 00346535. doi: 10.1162/rest.90.3.414.
- J Daoust, R Nadeau, R Dassonneville, E Lachapelle, E Bélanger, and J Savoie. How to survey citizens’ compliance with COVID-19 public health measures? Evidence from three survey experiments. 2020. URL <https://osf.io/preprints/socarxiv/gursd/>.
- Nabarun Dasgupta, Allison Lazard, Benjamin Eugene White, and Stephen W Marshall. Quantifying the social distancing privilege gap : a longitudinal study of smartphone move-

- ment. pages 0–13, 2020. URL <https://www.medrxiv.org/content/10.1101/2020.05.03.20084624v1>.
- Paul Dolan and Daniel Kahneman. Interpretations of Utility and Their Implications for the Valuation of Health. *The Economic Journal*, 118(525):215–234, jan 2008. ISSN 0013-0133. doi: 10.1111/j.1468-0297.2007.02110.x. URL <https://academic.oup.com/ej/article/118/525/215-234/5088783>.
- Shuo Feng, Chen Shen, Nan Xia, Wei Song, Mengzhen Fan, and Benjamin J. Cowling. Rational use of face masks in the COVID-19 pandemic. *The Lancet Respiratory Medicine*, 8(May):434–436, may 2020. ISSN 22132619. doi: 10.1016/S2213-2600(20)30134-X.
- Susan Godlonton, Alister Munthali, and Rebecca Thornton. Responding to risk: Circumcision, information, and HIV prevention. *Review of Economics and Statistics*, 98(2):333–349, may 2016. ISSN 15309142. doi: 10.1162/REST_a_00516.
- Andrew Goodman-Bacon. Difference-in-Differences with Variation in Treatment Timing. *National Bureau of Economic Research*. ISSN 0898-2937. doi: 10.3386/w25018. URL <https://www.nber.org/papers/w25018.pdf>.
- Trisha Greenhalgh, Manuel B. Schmid, Laurence Gruer, Thomas Czypionka, Dirk Bassler, and Laurence Gruer. Face masks for the public during the covid-19 crisis. *The BMJ*, 369(April):1–4, apr 2020. ISSN 17561833. doi: 10.1136/bmj.m1435. URL <http://dx.doi.org/doi:10.1136/bmj.m1435><http://eprints.lse.ac.uk/104230/https://doi.org/10.1136/bmj.m1435lseresearchonline@lse.ac.ukhttps://eprints.lse.ac.uk/Reuse>.
- IMF. World Economic Outlook, April 2020: The Great Lockdown. Technical Report April, 2020. URL <https://www.imf.org/en/Publications/WE0/Issues/2020/04/14/weo-april-2020>.
- Frederik Jørgensen, Alexander Bor, and Michael Bang Petersen. Compliance Without Fear: Predictors of Protective Behavior During the First Wave of the COVID-19 Pandemic. 2020. URL <https://psyarxiv.com/uzwgf>.
- Shailendra Kapoor. The HPV Vaccine and Behavioral Disinhibition, jan 2008. ISSN 1054139X.
- Y. Li, H. Tokura, Y. P. Guo, A. S.W. Wong, T. Wong, J. Chung, and E. Newton. Effects of wearing N95 and surgical facemasks on heart rate, thermal stress and subjective sensations. *International Archives of Occupational and Environmental Health*, 78(6):501–509, jul 2005. ISSN 03400131. doi: 10.1007/s00420-004-0584-4.
- James G. MacKinnon and Matthew D. Webb. The wild bootstrap for few (treated) clusters. *The Econometrics Journal*, 21(2):114–135, jun 2018. ISSN 1368-4221. doi: 10.1111/ectj.12107. URL <https://academic.oup.com/ectj/article/21/2/114-135/5078969>.
- Thomas Mellan, H Hoeltgebaum, S Mishra, C Whittaker, and et al. Report 21 - Estimating COVID-19 cases and reproduction number in Brazil. Technical report, 2020. URL <https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/covid-19/report-21-brazil/>.
- Ted R. Miller and Glenn C. Blomquist. *The Regulation of Motor Vehicle and Traffic Safety*, volume 56. 1989. ISBN 9789401077101. doi: 10.2307/1059086.
- Sam Peltzman. The effects of automobile safety regulation: Reply. *Accident Analysis and*

- Prevention*, 8(2):139–142, 1976. ISSN 00014575. doi: 10.1016/0001-4575(76)90005-1. URL <https://www.jstor.org/stable/1830396>.
- RKI. Coronavirus Disease 2019 (COVID-19) Daily Situation Report of the Robert Koch Institute. Technical report, 2020. URL <https://corona.rki.de>.
- David Roodman, Morten Ørregaard Nielsen, James G. MacKinnon, and Matthew D. Webb. Fast and wild: Bootstrap inference in Stata using boottest. *The Stata Journal: Promoting communications on statistics and Stata*, 19(1):4–60, mar 2019. ISSN 1536-867X. doi: 10.1177/1536867X19830877. URL <http://journals.sagepub.com/doi/10.1177/1536867X19830877>.
- Paul Schrimpf, Hiroyuki Kasahara, and Victor Chernozhukov. Causal impact of masks, policies, behavior on early COVID-19 pandemic in the U.S. Technical report, Centre for Microdata Methods and Practice (cemmap), may 2020. URL <https://www.ifs.org.uk/publications/14863>.
- Gyula Seres, Anna Balleyer, Nicola Cerutti, Anastasia Danilov, Jana Friedrichsen, and Yiming Liu. Face Masks Increase Compliance with Physical Distancing Recommendations During the COVID-19 Pandemic. 2020. URL <https://osf.io/db8sj/>.
- Ned Stafford. Covid-19: Why Germany’s case fatality rate seems so low, apr 2020. URL <https://www.bmj.com/content/369/bmj.m1395>.
- Joop Van Der Pligt and Nanne K. De Vries. Expectancy-value models of health behaviour: The role of salience and anticipated affect. *Psychology and Health*, 13(2):289–305, 1998. ISSN 08870446. doi: 10.1080/08870449808406752. URL <https://www.tandfonline.com/action/journalInformation?journalCode=gps20>.
- Ian Walker. Drivers overtaking bicyclists: Objective data on the effects of riding position, helmet use, vehicle type and apparent gender. *Accident Analysis and Prevention*, 39(2): 417–425, mar 2007. ISSN 00014575. doi: 10.1016/j.aap.2006.08.010.
- Gregory A. Wellenius, Swapnil Vispute, Valeria Espinosa, Alex Fabrikant, and Thomas C. Tsai. Impacts of State-Level Policies on Social Distancing in the United States Using Aggregated Mobility Data during the COVID-19 Pandemic. *Harvard Global Health Institute, Cambridge, MA*, 2020.
- WHO. Coronavirus disease (COVID-19) Situation Report – 110. *World Health Organization*, 2019(March):2633, 2020. doi: 10.1001/jama.2020.2633. URL <https://www.who.int/emergencies/diseases/novel-coronavirus-2019>.

6 Online Appendix

A Implementation dates

Table A1: Implementation dates of compulsory face mask policies and other COVID-19 measures

State	Face mask policy	Lockdown relaxed	Sec. school open	Retail open < 800 m ²	All retail open	Restaurants open
Baden-Wuerttemberg	27/04/2020	11/05/2020	04/05/2020	20/04/2020	11/05/2020	18/05/2020
Bayern	27/04/2020	06/05/2020	27/04/2020	27/04/2020	11/05/2020	18/05/2020
Berlin	27/04/2020	09/05/2020	27/04/2020	22/04/2020	09/05/2020	15/05/2020
Brandenburg	27/04/2020	09/05/2020	27/04/2020	22/04/2020	09/05/2020	15/05/2020
Bremen	27/04/2020	13/05/2020	27/04/2020	20/04/2020	13/05/2020	18/05/2020
Hamburg	27/04/2020	13/05/2020	27/04/2020	20/04/2020	13/05/2020	13/05/2020
Hessen	27/04/2020	09/05/2020	27/04/2020	20/04/2020	09/05/2020	15/05/2020
Nieder-Sachsen	27/04/2020	11/05/2020	27/04/2020	20/04/2020	11/05/2020	11/05/2020
Mecklenburg-Vorpommern	27/04/2020	11/05/2020	27/04/2020	20/04/2020	02/05/2020	09/05/2020
Nordrhein-Westphalen	27/04/2020	11/05/2020	23/04/2020	20/04/2020	11/05/2020	11/05/2020
Rheinland-Pfalz	27/04/2020	13/05/2020	27/04/2020	20/04/2020	04/05/2020	13/05/2020
Saarland	27/04/2020	28/04/2020	04/05/2020	20/04/2020	04/05/2020	18/05/2020
Sachsen	20/04/2020	20/04/2020	20/04/2020	20/04/2020	15/05/2020	15/05/2020
Sachsen-Anhalt	23/04/2020	04/05/2020	23/04/2020	20/04/2020	04/05/2020	18/05/2020
Schleswig-Holstein	29/04/2020	09/05/2020	27/04/2020	20/04/2020	09/05/2020	18/05/2020
Thuringen	24/04/2020	13/05/2020	27/04/2020	24/04/2020	04/05/2020	15/05/2020

Note: Berlin made face masks compulsory on public transport on April 27 and in shops two days later. All other states made face masks compulsory on public transport and shops at the same time. *Face mask policy* refers to the first date when a state implemented a compulsory face mask policy (regardless of whether it applied to public transport, shops, or both). *Lockdown relaxed* refers to the first date when a state introduced a first easing of the stay-at-home orders (“Ausgangsbeschränkungen”), which varied somewhat between different states. *Secondary school open* refers to the first date when a state re-opened secondary schools for pupils in their final year (“Abschlussklassen”). The two *Retail open* columns record the first date where a state allowed retail shops < 800 m² and without any size restrictions to re-open. *Restaurants open* refers to the first date when a state allowed restaurants to re-open. *Sources:* Verordnungen der Landesregierungen, Bußgeldkatalog, national and local newspapers.

B Mobility trends

Figure A1 shows mobility trends in specific public spaces as well as in terms of hours spent in places of residence.

Figure A1: Mobility trends in Germany (other mobility measures)



Note: This graph shows the percentage change in mobility (shown separately for groceries and pharmacies, workplaces, places of residence, and transit stations) for each day between Feb 15th and May 21st 2020 relative to the baseline mobility for that day of the week. The baseline is the median value for the corresponding day of the week in the five-week period between Jan 3rd and Feb 6th 2020. *Data:* Google COVID-19 Community Mobility Reports.

C Static DD estimates for other mobility measures

This section presents estimates from the static DD model (Equation 1) for other location-specific mobility measures.

Table A2: Effect of compulsory face mask policies on mobility in groceries and pharmacies

	(1)	(2)	(3)	(4)	(5)	(6)
Face mask policy	-4.723*** (1.091)	-4.918*** (0.963)	-4.902*** (0.971)	-4.832*** (1.034)	-4.859*** (1.051)	-4.896*** (0.789)
State FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-specific holidays		✓	✓	✓	✓	✓
Lockdown relaxed		✓	✓	✓	✓	✓
COVID-19 cases (t-1)			✓	✓	✓	✓
Sec. school open				✓	✓	✓
Retail open					✓	✓
State * Day-of-week FE						✓
Observations	957	957	957	957	957	957
R-squared	0.951	0.962	0.962	0.962	0.962	0.984
Clusters	16	16	16	16	16	16

Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Effect of compulsory face mask policies on mobility in workplaces

	(1)	(2)	(3)	(4)	(5)	(6)
Face mask policy	2.129*** (0.714)	1.927** (0.810)	1.916** (0.801)	1.275 (0.986)	1.497 (1.017)	0.967 (0.833)
State FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-specific holidays		✓	✓	✓	✓	✓
Lockdown relaxed		✓	✓	✓	✓	✓
COVID-19 cases (t-1)			✓	✓	✓	✓
Sec. school open				✓	✓	✓
Retail open					✓	✓
State * Day-of-week FE						✓
Observations	960	960	960	960	960	960
R-squared	0.974	0.978	0.979	0.979	0.979	0.989
Clusters	16	16	16	16	16	16

Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Effect of compulsory face mask policies on mobility in transit stations

	(1)	(2)	(3)	(4)	(5)	(6)
Face mask policy	-0.094 (1.117)	-0.620 (0.978)	-0.630 (0.988)	-1.642 (1.259)	-1.614 (1.195)	-1.593* (0.907)
State FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-specific holidays		✓	✓	✓	✓	✓
Lockdown relaxed		✓	✓	✓	✓	✓
COVID-19 cases (t-1)			✓	✓	✓	✓
Sec. school open				✓	✓	✓
Retail open					✓	✓
State * Day-of-week FE						✓
Observations	960	960	960	960	960	960
R-squared	0.917	0.920	0.920	0.921	0.921	0.948
Clusters	16	16	16	16	16	16
Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1						

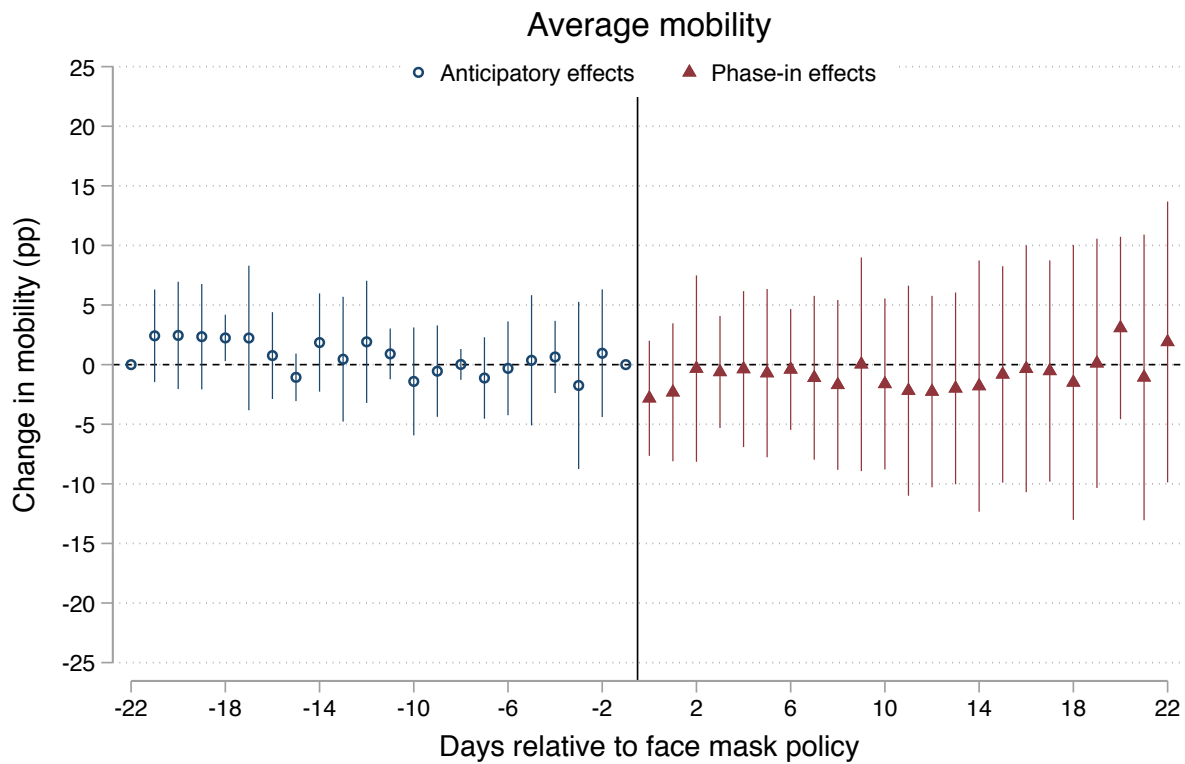
Table A5: Effect of compulsory face mask policies on time spent at home

	(1)	(2)	(3)	(4)	(5)	(6)
Face mask policy	0.083 (0.220)	0.257** (0.094)	0.255** (0.095)	0.445*** (0.134)	0.450*** (0.138)	0.222 (0.171)
State FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-specific holidays		✓	✓	✓	✓	✓
Lockdown relaxed		✓	✓	✓	✓	✓
COVID-19 cases (t-1)			✓	✓	✓	✓
Sec. school open				✓	✓	✓
Retail open					✓	✓
State * Day-of-week FE						✓
Observations	960	960	960	960	960	960
R-squared	0.973	0.975	0.975	0.975	0.975	0.985
Clusters	16	16	16	16	16	16
Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1						

D Parallel trends

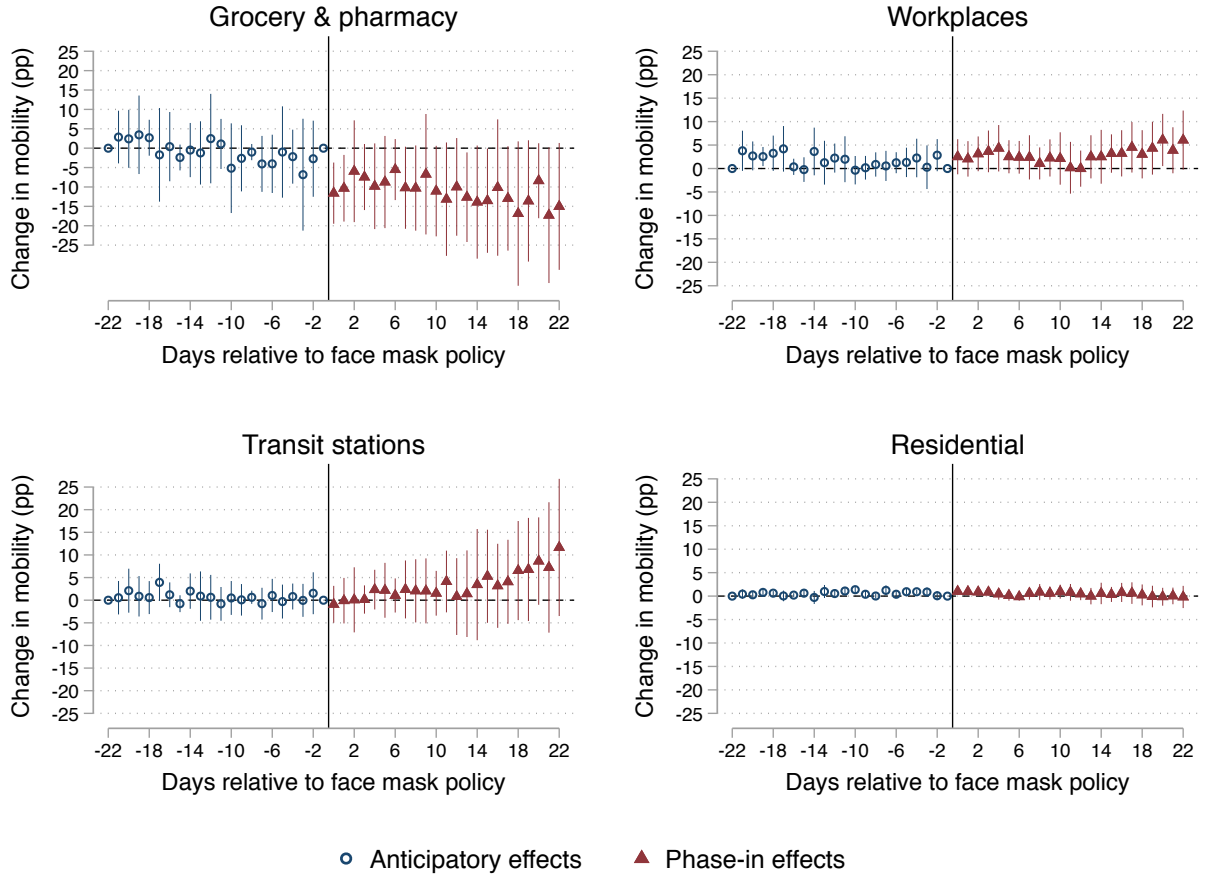
This section examines parallel trends using the fully dynamic event study specification (Equation 2).

Figure A2: Fully dynamic event study estimates for average mobility in public spaces



Note: This graph shows the estimated anticipatory and over-time effects of compulsory face mask policies on average mobility in public spaces (groceries and pharmacies, workplaces, and transit stations) for 22 days before and after the policy change. Point estimates are obtained from a fully dynamic event study model, where the first and last treatment leads are set to zero and the panel is “trimmed” such that it is balanced in time periods (days) relative to the policy change. Vertical lines represent cluster-robust 95% confidence intervals.

Figure A3: Fully dynamic event study estimates for other mobility measures

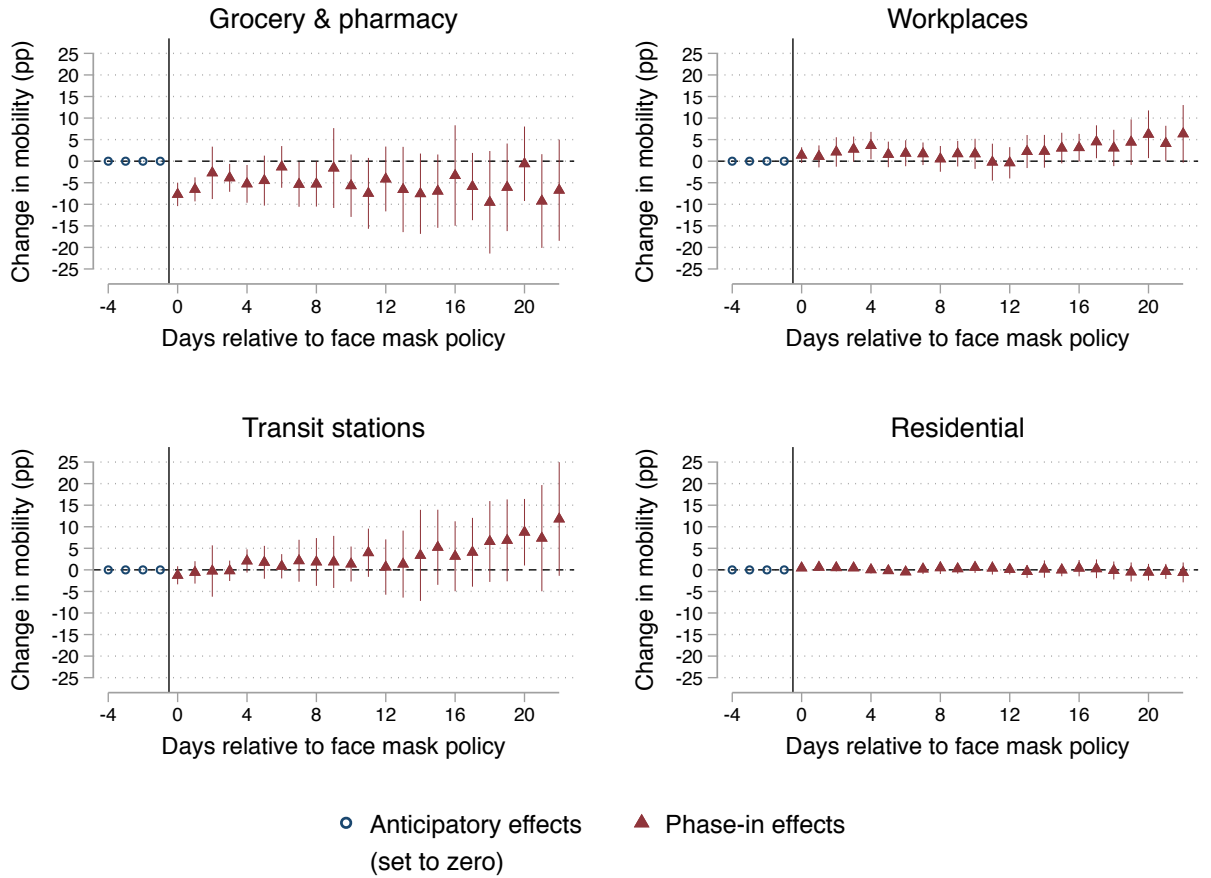


Note: This graph shows the estimated anticipatory and over-time effects of compulsory face mask policies on mobility (shown separately for groceries and pharmacies, workplaces, transit stations, and places of residence) for 22 days before and after the policy change. Point estimates are obtained from a fully dynamic event study model, where the first and last treatment leads are set to zero and the panel is “trimmed” such that it is balanced in time periods (days) relative to the policy change. Vertical lines represent cluster-robust 95% confidence intervals.

E Semi-dynamic estimates for other mobility measures

Figure A4 shows semi-dynamic event study (see Equation 3) estimates for measures of mobility in specific public spaces as well as hours spent in places of residence.

Figure A4: Semi-dynamic event study estimates for other mobility measures



Note: This graph shows the estimated over-time effects of compulsory face mask policies on mobility (shown separately for groceries and pharmacies, workplaces, transit stations, and places of residence) for 22 days after the policy change. Point estimates are obtained from a semi-dynamic event study model, where all treatment leads are set to zero and the panel is “trimmed” such that it is balanced in time periods (days) relative to the policy change. Vertical lines represent cluster-robust 95% confidence intervals.

F Robustness checks

F.1 Fully dynamic binned specification

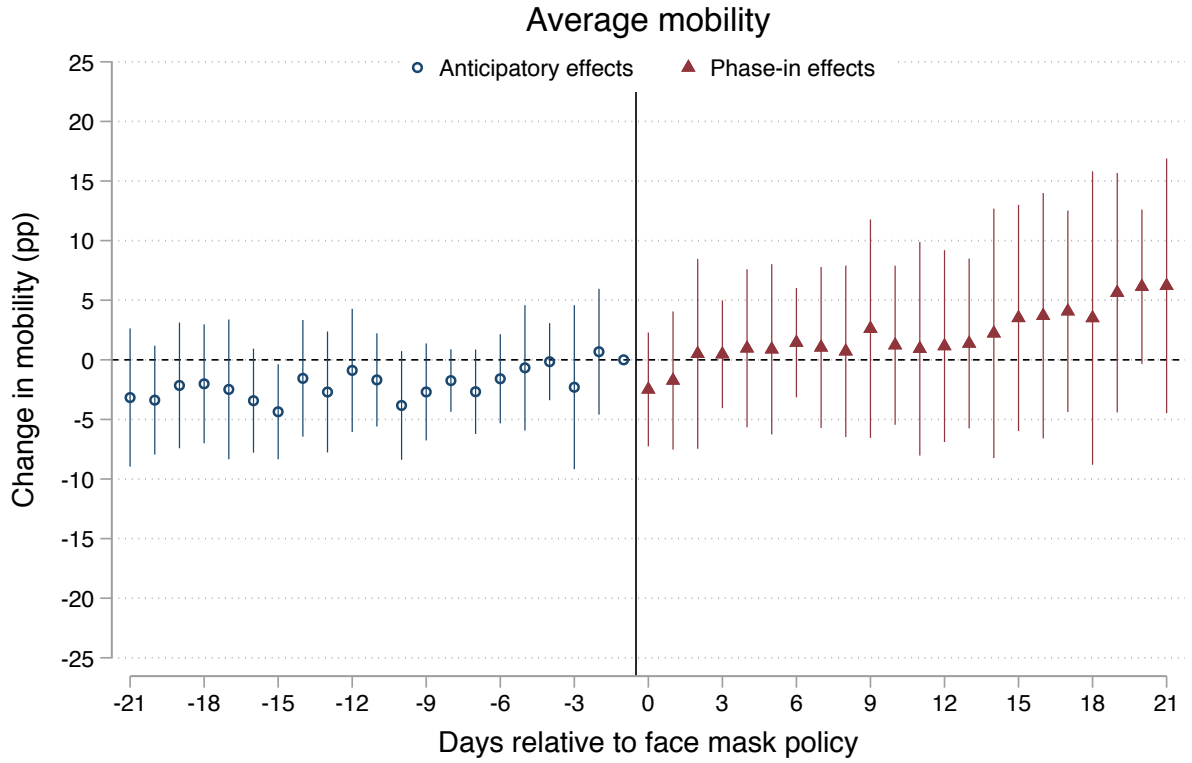
The fully dynamic binned model is specified as follows:

$$Y_{st} = \alpha_s + \beta_t + \mu_{\underline{g}} \sum_{\ell < -21} D_{st}^{\ell} + \sum_{\ell = -21}^{-2} \gamma_{\ell} D_{st}^{\ell} + \sum_{\ell = 0}^{21} \gamma_{\ell} D_{st}^{\ell} + \mu_{\bar{g}} \sum_{\ell > 21} D_{st}^{\ell} + X'_{st} + \epsilon_{st} \quad (4)$$

where distant relative periods ($|\ell| > 21$) are binned into $\underline{g} = [-T, -21)$ and $\bar{g} = (21, T]$ and T denotes all available calendar time periods (i.e. dates) in the data. In the binned specification, the panel is balanced in calendar time periods rather than in periods relative to the treatment. Only one lead (where $\ell = -1$) is set to zero.

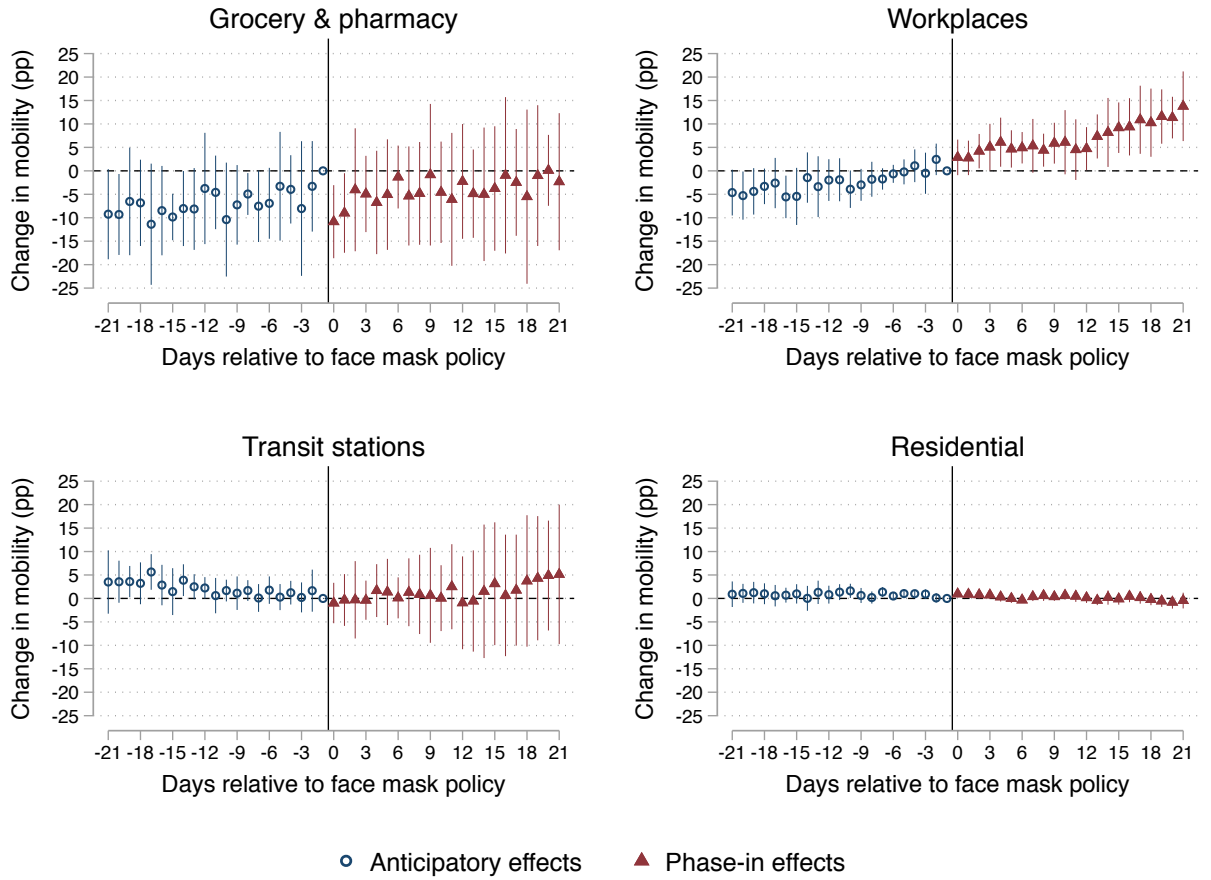
Figures [A5](#) and [A6](#) show, respectively, estimates from fully dynamic “binned” event study models for measures of average mobility and mobility in specific locations.

Figure A5: Fully-dynamic binned event study estimates for average mobility



Note: This graph shows the estimated anticipatory and over-time effects of compulsory face mask policies on average mobility (groceries and pharmacies, workplaces, transit stations) for 22 days before and after the policy change. Point estimates are obtained from a fully-dynamic event study model, where the first treatment lead is set to zero. The most distant leads and lags are “binned” and not displayed. The panel is balanced in calendar time periods. Vertical lines represent cluster-robust 95% confidence intervals.

Figure A6: Fully-dynamic binned event study estimates for other measures of mobility



Note: This graph shows the estimated anticipatory and over-time effects of compulsory face mask policies on mobility (shown separately for groceries and pharmacies, workplaces, transit stations, and places of residence) for 22 days before and after the policy change. Point estimates are obtained from a fully-dynamic event study model, where the first treatment lead is set to zero. The most distant leads and lags are “binned” and not displayed. The panel is balanced in calendar time periods. Vertical lines represent cluster-robust 95% confidence intervals.

F.2 Never-treated control group

We re-run the main static DD specification (Equation 1) using a control group of states that are never exposed to the treatment. Given that all states in Germany eventually implemented compulsory face mask policies, we create an “artificial” control group. To this end, we drop all observations from April 27th onwards. The four states that made face masks compulsory before April 27th now constitute the treatment group and the remaining twelve states are part of the artificial never-treated control group.

Table A6: Effect of compulsory face mask policies on mobility in public spaces (with never-treated control group)

	(1)	(2)	(3)	(4)	(5)	(6)
Face mask policy	0.860 (1.013)	0.080 (1.463)	0.147 (1.495)	0.136 (1.714)	0.111 (1.697)	-1.090 (1.455)
State FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-specific holidays		✓	✓	✓	✓	✓
Lockdown relaxed		✓	✓	✓	✓	✓
COVID-19 cases (t-1)			✓	✓	✓	✓
Sec. school open				✓	✓	✓
Retail open					✓	✓
State * Day-of-week FE						✓
Observations	560	560	560	560	560	560
R-squared	0.971	0.971	0.971	0.971	0.971	0.986
Clusters	16	16	16	16	16	16
Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1						

F.3 Wild cluster bootstrap

We employ a wild cluster bootstrap procedure to obtain more accurate p-values. Intuitively, the procedure generates many bootstrap samples that mimic the distribution from which the original sample was obtained. It then computes a t-statistic for the coefficient of interest in each bootstrap sample. The refined p-value is the proportion of the bootstrap t-statistics that are more extreme than the t-statistic obtained from the original sample [Angrist and Pischke, 2009].

In a setting with very few treated clusters, the standard wild cluster bootstrap will typically under-reject the null of no treatment effect when the null is imposed (restricted). The restricted specification is the one from which we obtain the refined p-values reported in the main results table (Table 1). In contrast, the standard wild cluster bootstrap will over-reject when the null is not imposed (unrestricted) [MacKinnon and Webb, 2018, Roodman et al., 2019]. To account for this problem, we also employ the “sub-cluster” wild bootstrap procedure proposed by MacKinnon and Webb [2018], where the wild bootstrap data-generating process is clustered at a finer level (i.e. state-date level) than the covariance matrix (i.e. state level).

In Table A7 we report results from static DD models predicting our main outcome (average mobility), with refined p-values from a wild cluster bootstrap procedure, where the data-generating process is clustered at the state-date level (and the null is imposed).

Table A7: Effect of compulsory face mask policies on mobility in public spaces

	(1)	(2)	(3)	(4)	(5)	(6)
Face mask policy	-0.759 (0.703) [0.366]	-1.075 (0.692) [0.211]	-1.074 (0.700) [0.214]	-1.591 (0.946) [0.211]	-1.500 (0.924) [0.228]	-1.763** (0.605) [0.040]
State FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-specific holidays		✓	✓	✓	✓	✓
Lockdown relaxed		✓	✓	✓	✓	✓
COVID-19 cases (t-1)			✓	✓	✓	✓
Sec. school open				✓	✓	✓
Retail open					✓	✓
State * Day-of-week FE						✓
Observations	960	960	960	960	960	960
R-squared	0.965	0.973	0.973	0.973	0.973	0.985
Clusters	16	16	16	16	16	16

Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
 Wild cluster (state-date level) bootstrap p-values in square brackets.

F.4 State-week clustered standard errors

We re-run the main static DD specification (Equation 1) using robust standard errors clustered at the state-week level (rather than the state-level).

Table A8: Effect of compulsory face mask policies on mobility in public spaces (with robust standard errors clustered at the state-week level)

	(1)	(2)	(3)	(4)	(5)	(6)
Face mask policy	-0.759 (1.218)	-1.075 (1.228)	-1.070 (1.230)	-1.588 (1.480)	-1.494 (1.513)	-1.763** (0.844)
State FE	✓	✓	✓	✓	✓	✓
Date FE	✓	✓	✓	✓	✓	✓
State-specific holidays		✓	✓	✓	✓	✓
Lockdown relaxed		✓	✓	✓	✓	✓
COVID-19 cases (t-1)			✓	✓	✓	✓
Sec. school open				✓	✓	✓
Retail open					✓	✓
State * Day-of-week FE						✓
Observations	960	960	960	960	960	960
R-squared	0.968	0.976	0.976	0.976	0.976	0.987
Clusters	144	144	144	144	144	144

Robust standard errors clustered at the state-week level in parentheses.

*** p<0.01, ** p<0.05, * p<0.1