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Prolonged exposure weakens risk perception and behavioral mobility response: Empirical evidence from Covid-19

A. Stechemesser[a,b], M. Kotz[a,b], M. Auffhammer[c,d,e], L. Wenz[a,f,*]

[a] Potsdam Institute for Climate Impact Research, Potsdam, Germany
[b] Institute of Physics, Potsdam University, Potsdam, Germany
[c] Department of Agricultural and Resource Economics, University of California Berkeley, Berkeley, CA, USA
[d] Energy Analysis and Environmental Impacts Division, Lawrence Berkeley National Laboratory, Berkeley, CA, USA
[e] National Bureau of Economic Research, Cambridge, MA, USA
[f] Mercator Research Institute on Global Commons and Climate Change, Berlin, Germany

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ABSTRACT

Understanding the behavioral response dynamics to risks is important for informed policy-making at times of crises. Here we elucidate two response channels to Covid-19 risk and show that they weakened over time, prior to the availability of vaccines. We employ fixed-effects panel regression models to empirically assess the relationship between actual Covid-19 risk (daily case numbers), the perceived risk (attention paid to the pandemic via related Google search requests) and the resulting behavioral response (personal mobility choices) over two pandemic phases for 113 cities in eight countries, while accounting for government interventions. Prolonged exposure to Covid-19 reduces risk perception which in turn leads to a weakened behavioral response. Attention responses and mobility reductions across all three mobility types are weaker in the second phase, given the same levels of actual and perceived risk, respectively. Our results provide evidence that the risk response attenuates over time with implications for other crises evolving over long timescales.

1. Introduction

Understanding the behavioral response of individuals to systemic as well as personal risks is key for assessing the scope and effectiveness of societal adaptation and identifying the need for effective policy-interventions. Individuals navigate risk-based tradeoffs between personal costs and benefits which impact not only themselves but also society more broadly. Profound systematic threats such as the spread of infectious diseases or anthropogenic climate change unfold on longer timescales and require both sustained awareness and behavioral adjustment from individuals such as engagement with public interventions designed to mitigate risk (e.g. compliance with preventive health interventions). Meta-analyses as well as experimental and observational studies suggest that the perception of risk is a decisive factor for behavioral change (Ferrer and Klein, 2015; Sheeran et al., 2014). However, risk perception can evolve dynamically over time as individuals reevaluate risks and the estimated impacts on their lives as more information becomes available or their priorities shift (Loewenstein and Mather, 1990; Betsch et al., 2020). Moreover, personal risk perception does not necessarily reflect an objective risk as it is influenced by a number of complex psychological and emotional factors (Loewenstein and Mather, 1990; Slovic et al., 1980; Wang et al., 2022; Duong et al., 2021; Man et al., 2019; Bavel et al., 2020; Gollwitzer et al., 2020). Understanding the evolution of risk perception over time and the resulting behavioral patterns is key for designing policy interventions which remain effective as personal responses evolve. At the same time a robust assessment of risk responses is challenging due to data constraints and a complex landscape of possible personal adaptation measures to a number of health and environmental risks.

The outbreak of the Covid-19 pandemic presents a crucial opportunity to obtain insights into behavioral responses to risk and to explore the dynamic development of risk perception after prolonged exposure. A growing body of evidence suggests that pre-existing risk perceptions shaped behavioral responses to Covid-19 (Qin et al., 2021; Chan et al., 2020; Schneider et al., 2021; Savadori and Lauriola, 2020). After the outbreak of the pandemic, risk perception increased (Neuburger and Egger, 2021; Wise et al., 2020), leading for example to low travel intentions, high compliance with preventive measures and an intention to

* Corresponding author at: Potsdam Institute for Climate Impact Research, Potsdam, Germany.
E-mail address: leonie.wenz@pik-potsdam.de (L. Wenz).

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accept a vaccine once it became available (Caserotti et al., 2021). However, the dynamic development of risk perception over time and the resulting behavioral impacts generally and more specifically in the case of Covid-19 are still understudied (Wang et al., 2021; Leppin and Aro, 2009). The majority of existing time series analyses of Covid-19 focus on observational data from two to four time points between January and August 2020 or cover one place or country only (Wang et al., 2021; Savadori and Lauriola, 2022; Kashima and Zhang, 2021; Dönges et al., 2022).

Here we use the Covid-19 pandemic to empirically assess the relationship between weekly actual risk, risk perception and behavioral responses for 113 cities in eight countries from April 2020 to March 2021. As of March 2021, the World Health Organization had confirmed more than 116 million reported Covid-19 cases and more than 2.7 million deaths worldwide (WHO, 2023b). This international emergency constitutes a particularly suitable case study for quantitatively investigating risk responses across countries for three main reasons. First, the virus newly emerged and spread rapidly around the world, posing a comparable threat to all countries included in the study. Second, during the timeframe of the pandemic assessed in this study (April 2020 to March 2021), vaccines were not available to the general public. With no known effective medicines available, prevention and self-protection were the only feasible risk mitigation responses, yielding a clear rational behavioral response to the threat posed by Covid-19: Social distancing, reducing personal contact and staying at home. This makes the Covid-19 pandemic suitable to empirically measure risk mitigation behavior as opposed to other threats where strategies to mitigate risk might vary. Third, the Covid-19 pandemic prominently disrupted nearly every aspect of everyday life for more than one year before vaccines became available, making it a suitably long time period to study the dynamic response of risk perception and behavioral response, including potential risk normalization. Risk normalization describes the process of gradually lowering perception of a risky or dangerous behavior or circumstance such that it becomes acceptable over time (Lima et al., 2005; Parkhill et al., 2010) and is for example explained as a psychological response to cope with prolonged exposure to a threat (Lima et al., 2005; Lima, 2004; Richardson et al., 1987).

Our empirical approach is embedded in a simple theoretical framework (Fig. 1) based on three main components: actual risk, risk perception and behavioral response. Actual risk is measured using the weekly total of new Covid-19 cases per 100,000 inhabitants in each city which we assemble from a variety of public data sources (compare SI Appendix, Section 1, Table S1). Following recent literature (Barrios and Hochberg, 2021; Ahundjanov et al., 2021; 2020), we use attention paid to the Covid-19 pandemic as an indicator for the perceived risk. Specifically, we employ Google Trends to extract the weekly number of Google searches for a number of pandemic-related keywords (“Covid”, “Corona”, “Covid-19”, “Covid19”, “Coronavirus”) on the smallest geographic resolution available for each city (compare Materials and Methods, SI Appendix, Section 1, Table S2). With a market share of more than 90% and handling more than 2 trillion search requests every year (Parmy Olson, 2022), Google is by far the most popular search engine. Google Trends data have been used to empirically analyze attention patterns and behavioral changes such as spatiotemporal trends in food poverty (Eskandari et al., 2019), impact of the Olympic games on physical activity (Bauman et al., 2021), trading behavior in financial markets (Preis et al., 2013), awareness to poor air quality (Burke et al., 2022) or antipsychotic drug search intensities (Ågren, 2021). In the context of Covid-19, Google Trends data have been used, inter alia, in machine learning models that forecast pandemic hotspot locations (Ward et al., 2022), to compute measures of well-being in Chile (Díaz et al., 2022) and changes in pornography habits during quarantine (Zattoni et al., 2021). In our analysis of Google Trends data we start our attention time series in mid-April, when all countries included in the analysis reported multiple thousand cumulative cases (Our World in Data, 2023b). We choose this start date rather than the emergence of the first Covid-19 cases because the general novelty of the virus caused excessive global attention prior to the relevance of local pandemic risk. Time-series of Covid-19 searches show a peak and decline in Google searches across countries prior to this date, indicating that our choice limits the potential bias of global interest in the pandemic (see SI Appendix section 3.j for details). Our main findings are qualitatively robust to this specific choice of start date (see SI Appendix, Fig. S19). Google requests containing the chosen keywords (“Covid”, “Corona”, “Covid-19”, “Covid19”, “Coronavirus”) are provided by Google Trends in a normalized format ranging from zero to 100, where 100 corresponds to the day with the maximum search requests in a location and the timeframe of interest (here April 2020 to March 2021). The variable can therefore be interpreted as the weekly search interest as percent of the maximum search interest. Finally, we employ mobility data to assess the behavioral response. Social distancing and stay-at-home measures were the dominant strategies to contain Covid-19 before the availability of vaccines, engagement with which are both reflected clearly in reductions in personal mobility (Haug et al., 2020; Arenas et al., 2020; Hsiang et al., 2020; Chinazzi et al., 2020; Kraemer et al., 2020; Tian et al., 2020; Ku et al., 2021; Kraus and Koch, 2021). Moreover, survey-based, regional studies (Wang et al., 2021; Hotle et al., 2020; Parady et al., 2020; Airak et al., 2023) indicate that higher risk perception is

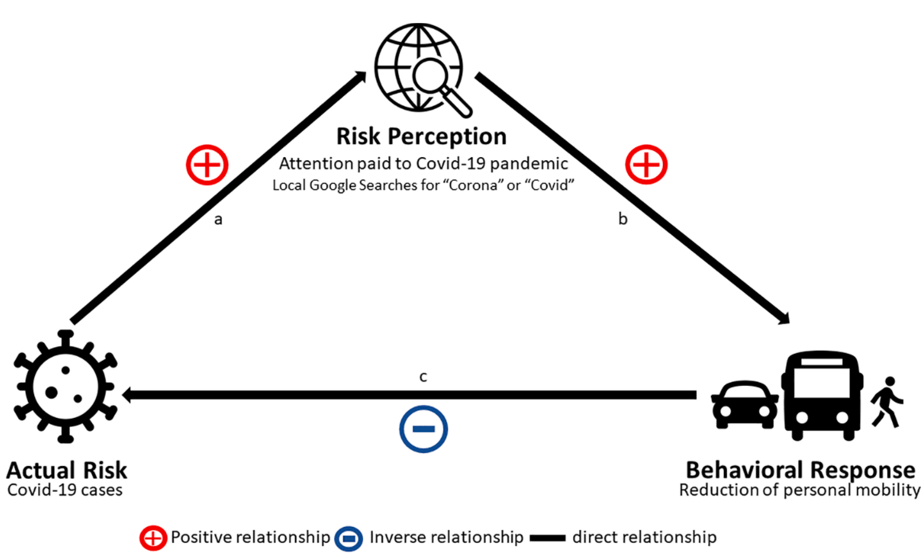

Fig. 1. The theoretical framework underlying the empirical assessment of the overall risk response. *We hypothesize that Covid-19 cases pose the actual risk. If Covid-19 cases increase the perceived risk increases (positive impact). The perceived risk is approximated by attention paid to the Covid-19 pandemic, measured as Google search requests for the terms “Covid”, “Corona”, “Covid-19”, “Covid19” or “Coronavirus”. We further hypothesize that, if risk perception is high, there is a stronger behavioral response (positive impact), implying reductions in personal mobility as individuals adjust their behavior to avoid the risk. Previous research has shown that, if the behavioral response increases, contact is avoided and cases decrease (inverse impact). Overall, we obtain a negative feedback loop in which a higher risk perception inhibits the spread of Covid-19. (icons: Flaticon.com)*

associated with reduced mobility, providing further foundation for the choice of mobility changes as a measure of behavioral changes to risk. Data on personal mobility comprise the daily percentage changes in private vehicle, public transportation and pedestrian use in comparison to a pre-pandemic reference day recorded by Apple Maps (Apple, 2021).

Our theoretical framework (Fig. 1) addresses the impact of the subjective risk perception on behavior by separately assessing the response of risk perception to actual risk and the behavioral response to risk perception. This framework hypothesizes a positive effect of the level of actual risk (new Covid-19 cases) on the level of perceived risk (attention paid to pandemic via Google search requests, Fig. 1, arrow a), as well as a positive impact of the perceived risk on the behavioral response. In our analysis a strong behavioral response means a strong mobility reduction (Fig. 1, arrow b). A direct impact of behavioral changes, specifically changes in mobility, on case numbers (Fig. 1, arrow c) has been identified in previous literature with more protective behavior leading to smaller case numbers (Kraemer et al., 2020; Ilin et al., 2021; Soucy et al., 2020; Levy et al., 2022).

From the time series alone, considerable changes in attention paid to the pandemic and personal mobility are notable for all countries, with periods of high case numbers generally coinciding with high attention and personal mobility reductions (Fig. 2). We empirically validate the theoretical framework using fixed effects panel regression models. In all our models we explicitly account for government policy interventions, as non-pharmaceutical interventions had a large impact on both mobility behavior and attention paid to the pandemic. To this end, we use data on the stringency of governmental interventions regarding Covid-19 which is provided by the Oxford Covid-19 government response tracker (Hale et al., 2021). This measure is a combination of different indicators documenting the strictness of various government policies which primarily restrict the behavior of the population such as movement restrictions, transport closures, gathering restrictions or closures of schools and other facilities of public life. It has been used, for instance, to control for lockdown interventions in studies linking meteorological factors to Covid-19 transmission (Sera et al., 2021) or analyzing the impact of Covid-19 on global trade (Verschuur et al., 2021). We control for these policy measures in a number of ways: by including all indicators separately (Fig. S7), focusing specifically on the indicators most related to mobility change (Fig. S8), as well as by using a Principal Component Analysis to obtain composite indicators which contain over 60% of variation in the policy data (Figs. S10, S11). Our results are robust to these alternative ways of controlling for government interventions. Furthermore, we include city fixed effects to control for time-invariant differences between cities. In the model estimating the relationship between perceived risk and mobility we additionally consider controls for weekly Covid-19 cases, daily maximum temperature and precipitation as well as a season dummy to capture potential risk-independent weather and seasonal influences on the mobility behavior.

We interact the principal independent variable of interest (actual risk as Covid-19 cases or perceived risk measured as attention for Covid-19) with a pandemic phase dummy to estimate the impacts for two distinct phases that mark the developments of the pandemic. For simplicity, we consider two main pandemic phases: a *primary* phase directly following the local outbreak of the disease, and a *later* phase following a period of relatively low case numbers (often over the summer of 2020). These phases are identified algorithmically for each country (see Materials and Methods) and indicated by the green horizontal lines in Fig. 2.

2. Materials and methods

Here we give an overview of the data used in this study and of our empirical strategy.

2.1. Covid-19 case data – Acquisition and preprocessing

For each city included in this analysis we start with data on daily cumulative Covid-19 cases which are considered either on city level resolution or on the next higher local organizational structure (municipality, county) depending on data availability. A map showing all the cities included in the analysis is included in the SI Appendix, Section 1, Fig. S1. A table displaying the specific resolution and data source for each country can be found in the SI Appendix, Section 1, Table S1. We use Covid-19 cases as the principle measure for danger from Covid-19. A possible alternative would be to use Covid-19 mortality data. However, Covid-19 mortality data are subject to similar reporting errors but may contain additional errors (Van Noorden, 2022; Miller et al., 2022) as the attribution of deaths to Covid-19 has been shown to vary across countries and time (WHO, 2023a; Our World in Data, 2023a), especially in the earlier stages of the pandemic. In general, Covid-19 case and mortality data show very similar trends over time (SI Appendix, Section 3.i, Fig. S17).

The daily number of new cases for each city is computed as the difference between the cumulative cases on day d and the cumulative cases on the previous day $d-1$. If this difference is negative, measurement errors have occurred in the cumulative case data and the affected day is excluded from the analysis. Large spikes in the timeseries can also occur and may be due to delayed reporting in the number of cases. To identify these possible additional measurement errors, we apply a simple algorithm to detect outliers in their local environment. First, we identify days on which case numbers are more than 3.0 median absolute deviations away from the median of the data, a common methodology in the literature (Leys et al., 2013). The median absolute deviation approach (MAD) was first introduced by Leys et al. (2013) and has been found to be more robust in comparison to, for example, standard deviations away from the mean. All days identified with the MAD approach are labeled as potential outliers. A second MAD outlier detection is performed on a 20-day window centered on each of these days. Only if this day is again labeled as an outlier, is it removed. This process, which is also visualized in the SI Appendix, Section 2, Fig. S3, ensures that local outliers are detected and removed in a computationally efficient way, despite the large variation in the time series.

For each city, population data are used on the same resolution as the case data (see SI Appendix, Section 1, Table S1) to compute the daily new cases per 100,000 inhabitants. This normalization ensures comparability between the differently sized cities. Finally, we compute the weekly average of new Covid-19 cases per 100,000 inhabitants which is used as the main variable of interest in the empirical analysis. Using the weekly aggregation is more robust against reporting errors and delays in comparison to daily case data and matches the resolution of the Google search data.

2.2. Google search data

We employ Google Trends ("Google Trends", 2023) to extract the attention paid to the Covid-19 pandemic. Google Trends provides an anonymized, categorized and aggregated sample of Google search data (Rogers, 2016). We use the search words "Covid", "Corona", "Covid-19", "Covid19" and "Coronavirus" such that all web search requests that contain either term are included in the timeseries. The search terms are specific enough to very likely only capture attention related to the Covid-19 pandemic and at the same time generic enough that all types of pandemic-related inquiries are included. By contrast, it is not possible to use the names of specific Covid-19 variants that evolved over the course of 2020/2021 as sole search words: The search terms "alpha" and "delta" do not necessarily indicate attention for the Covid-19 pandemic as they are related to a number of other popular search requests in the time period of interest (compare SI Appendix, Section 1, Table S3 for details). Unlike other language related to Covid-19 such as "pandemic", "mask" etc., the terms "Covid", "Corona", "Covid-19", "Covid19" and

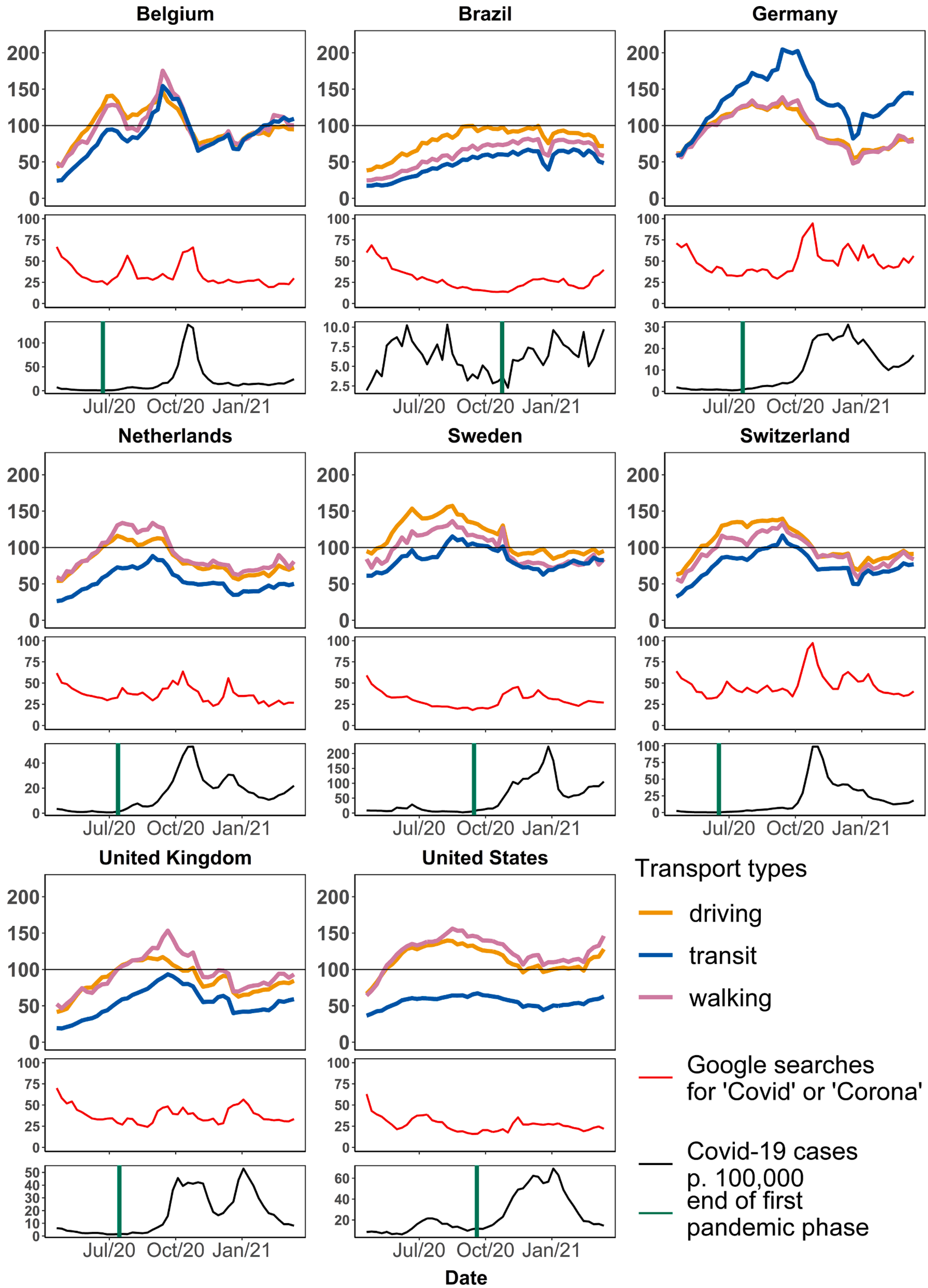

Fig. 2. Time series of personal mobility (driving, walking, transit), Google searches related to the pandemic and Covid-19 cases from April 2020 to March 2021 by country. *The country time series are computed as the population-weighted average of the time series for all cities in the country included in the data. The mobility data consist of navigation requests made to Apple maps for three different transport types (driving, walking, transit) and are reported as deviations of a baseline day before the outbreak of Covid-19 (13th January 2020). Weekly Google searches for "Covid", "Corona", "Covid-19", "Covid19" or "Coronavirus" are reported as percentage changes with respect to the maximum search requests in the observation period. The time series of Covid-19 cases for each country shows new cases per 100,000 inhabitants. The green line marks the algorithmically detected end of the first pandemic phase. The phases are identified on the country-level as opposed to the city-level as policies and the overall pandemic dynamic are likely to affect a country on the national level.* (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

"Coronavirus" are used internationally which enables comparisons across languages.

The highest available spatial resolution of the search data differs by country and region. For each city, search data on the highest available resolution are used, which usually corresponds to the county level for the United States and to the region or state level for the other countries included in this analysis. Details are provided in the SI Appendix, Section 1, Table S2. We use data at the highest temporal resolution available, which is weekly. Google Trends does not provide information on the raw requests but the data are scaled between zero and 100, where 100 corresponds to the maximum search interest for the time and location selected. Due to this relative normalization, the timespan for which the data are scraped makes a difference as the maximum might change. We extract all data from the week starting on 5th April 2020 to the week starting on March 14th 2021. The start date of the analysis is April 19th 2020 to avoid the influence of large-scale international pandemic-related incidents at the beginning of the Covid-19 outbreak. Please refer to the SI Appendix section 3.j, Fig. S18 for further discussion and robustness checks on the start date. The end date is informed by the advancements of the Covid-19 vaccination campaigns. Because of the scaling of the data we do not have any information about the total search volumes and cannot compare absolute interest across cities and countries. However, we can make statements about how the local trends evolve in comparison to each other.

As Google processes billions of search queries, requests for non-real-time data from Google Trends, like those used in this study, are answered with a random sample of the data. There has been some evidence of inconsistencies in the trends depending on which sample batch the user is assigned (Behnen et al., 2020). To ensure robustness in our data, we scrape the same timeseries multiple times on different days and using different IP addresses to get allocated a different batch of trends data. For each city, we assemble thirteen realizations of the timeseries and generate multiple country-level timeseries, averaging over possible combinations of the city-level data. The results show very limited variation for the search terms in which we are interested (see SI Appendix, Section 1, Fig. S2).

2.3. Transportation trend data

The data on personal mobility trends used in this study originate from the mobility trends reports data set collected and published by Apple (2021). For three different transportation types – driving, walking and transit – the daily percentage change of requests for directions in Apple Maps is reported. Given that the mobility data are reported as the percentage change from a reference day for each type of transport mode separately, they do not allow insights into mode switching. The first day of reporting is January 13th 2020 which provides the reference day. However, our analysis is centered from April 2020 to March 2021 when the urgency of the local pandemic development dominated global news related to Covid-19. For all timeseries, we compute the weekly average to match the temporal resolution of the Google search data. The mobility data set comprises instances on different levels of granularity such as the country, region and city levels. In this study we only consider cities for which all three forms of transport are reported and for which daily Covid-19 case data are available on a high resolution. This results in data from 113 cities in eight countries. Six out of the eight countries are European (Belgium, Germany, Netherlands, Sweden, Switzerland, United Kingdom), with the remaining countries originating from a different continent each (Brazil, United States).

2.4. Algorithmic identification of pandemic phases

Countries have experienced the Covid-19 pandemic in distinct phases. In this study, we focus on the differences between the first Covid-19 wave, which started immediately after the local outbreaks of the disease (mid-January to late-February for all countries included in this study), and a later phase which for most countries started sometime after the summer of 2020, at different times across countries. Doing so allows us to compare behavioral responses across countries prior to the widespread availability of vaccines which changed optimal self-protection strategies and personal risk levels.

We distinguish the first and later pandemic phases based on the identification of peaks in the number of new cases for each country, as policy interventions and general pandemic trends often have national effects. To that end, a shared, daily country time series based on all the cities of each country is computed as follows:

$$cases_{C,d} = \frac{\sum_{m=1}^{n} cases_{m,d}}{\sum_{m=1}^{n} pop_m} \cdot 100,000 \tag{1}$$

where $cases_{C,d}$ denotes the new cases per 100,000 in country C on day d and n stands for the number of cities in country C included in the analysis. $cases_{m,d}$ denotes the new cases in city (municipality) m on day d and pop_m corresponds to the population of city m, having applied the preprocessing described above.

The resulting time series for each country are then further smoothed using a triangular moving average with filter size 7, corresponding to an aggregation over the course of one week. Compared to a simple moving average the triangular moving average results in less noise while retaining peaks. Next, we identify local peaks in the timeseries using the "findpeaks()" algorithm of the R package pracma ("Package PRACMA" [2014] 2021). For the peaks, we apply two restrictions: First, that the minimum height of a local peak is larger or equal to the 25th quartile. Second, that the distance between two local peaks amounts to at least 100 days. The beginning of the first pandemic wave is set to be April 19th 2020 in the main analysis. The end is defined as the minimum in cases between the first and the second identified peak. The country time series and pandemic waves are shown in Fig. 2, the algorithmic identification of the cutoff date is visualized in the SI Appendix, Fig. S4.

2.5. Covid-19 government response controls

The data on government policy measures with regard to Covid-19 originate from the Oxford Covid-19 Government Response Tracker (OxCGRT) (Hale et al., 2021) which tracks 23 indicators in five different groups (Containment and closure policies, Economic policies, Health system policies, Vaccination policies, Miscellaneous policies) for all countries and dates included in our analysis. It has been employed to control for policy influences in multiple other studies (e.g. (Haug et al., 2020; Sera et al., 2021; Petherick et al., 2021; Duan et al., 2021)). All indicators are described in detail in the OxCGRT codebook (2020a). In addition, the OxCGRT data set contains aggregated indices summarizing different aspects of the government response, measured as the number of relevant indicators the government has acted upon as well as the degree of the response, in a single number (0–100). In order to control for the effect of government policy on mobility behavior we use the "stringency" index which records the strictness of the containment and closure policies (C1 to C8; OxCGRT codebook (2020a)) as well as the presence of public information campaigns (H1; OxCGRT codebook (2020a)). Using the stringency index allows us to effectively control for the impact of the most disruptive measures to mobility without causing collinearities in our models by including many indicators that are very similar. We take the weekly average of the stringency index in our main models to adjust it to the resolution of the Google search data. Information on how to calculate the specific indices can be found in the OxCGRT index methodology (Oxford Covid-19 Government Response Tracker, 2020b).

In the main specification we use the national stringency index for consistency. However, for three countries included in the analysis (Brazil, United Kingdom, United States) there is a subnational stringency index available. For these countries, we conduct a robustness analysis using subnational stringency (compare SI Appendix, Section 3.g,

Table S8, Fig. S13-S14), results of which agree with the main analysis.

As a further robustness check we conduct the analysis using the indicators C1 to C8 as individual controls (see SI Appendix, Section 3e, Fig. S7, Tables S6, S7). Additionally, we use indicators that directly affect local transport (public transport closure and internal movement restrictions) as explicit controls and combine the remaining indicators to a residual index (see SI Appendix, Section 3e, Fig. S8, S9). Finally, we perform a robustness check using a dimensionality-reduced representation of the different measures obtained through principle component analysis (see SI Appendix, section 3.f, Fig. S10, S11).

2.6. Population and climate data

To compute the new Covid-19 cases per 100,000 inhabitants it is necessary to pair the case data with population estimates for each location included in the analysis. The population data for each place are used at the same granularity as the case data (compare SI Appendix, Section 1, Table S1). Population data on city level originate from the *simplemaps* World Cities Database (Simplemaps, 2021) and the United Nations Statistics Division (UNdata, 2021). The county population data (2019) for the United States originate from the US census (2021).

In order to control for climate influences on the transport changes, the daily precipitation and daily maximum temperature for each city are approximated. We here use daily maximum temperature instead of daily average temperature to avoid bias through cold nights that have no influence on the mobility behavior in the day itself. Daily maximum 2m air temperature data on a 0.25-degree grid originate from the ERA-5 reanalysis data set (Dee et al., 2011). Daily precipitation data stem from the Global Precipitation Climatology Project (Bolvin et al., 2009; Huffman et al., 1997) and are also used on a 0.25-degree grid. Each city is approximated as a latitude-longitude point and paired with the daily precipitation and maximum temperature of the grid cell in which it falls. Daily precipitation and maximum temperature for each city are then aggregated to the weekly level to match the time resolution of the Google search data.

2.7. Empirical strategy

The goal of our empirical strategy is to measure the behavioral response to Covid-19 risk in two separate analyses: First we evaluate the impact of the actual risk (Covid-19 cases per 100,000) on the perceived risk (attention paid to the pandemic, Google searches for “Covid”, “Corona”, “Covid-19”, “Covid19” and “Coronavirus”). Next, we assess the relationship between the perceived risk on a behavioral change (personal mobility behavior).

To assess the overall impact of the actual Covid-19 risk on the perceived risk, we apply a fixed effects panel regression model exploiting within-city changes in the weekly mean of new Covid-19 cases per 100,000 inhabitants (independent variable, $cases_{m,w}$ with m indicating municipalities (cities) and w standing for weeks) and analyzing the respective percentage change in risk perception of the pandemic (dependent variable, $R_{m,w}$, Google searches). $R_{m,w}$ expresses the weekly number of Google search requests for the search words as a percentage of the day with the maximum search requests in the timeframe. The inclusion of city fixed effects (σ_m) strengthens the inference of causality in the findings by limiting omitted variable bias arising from time-invariant differences between cities (Huntington-Klein, 2021; Auffhammer, 2018; Hsiang, 2016; Dell et al., 2013). Furthermore, the $S_{C,w}$ variable describes the stringency index (compare section 2.5) which is used to account for the strictness of government response measures to Covid-19 that likely affect attention patterns for each country C. To estimate the effect in the different pandemic phases, we interact dummy variables for the country-specific first (p_1) and second (p_2) phase with the independent variable. The coefficients α_1 and α_2 are the main coefficients of interest (Fig. 3, Overall results). The overall model thus reads as

$$R_{m,w} = \alpha_1 cases_{m,w} \cdot p_1 + \alpha_2 cases_{m,w} \cdot p_2 + \eta S_{C,w} + \sigma_m + \epsilon_{m,w}. \tag{2}$$

To conduct separate analyses for each country, the data are split and the same regression model is applied for each country individually (Fig. 3)

In a second step, we analyze the impact of the perceived risk, measured as attention paid to the pandemic, on mobility behavior using a similar fixed effects panel regression model. The dependent variable here is the percentage change in Apple maps direction requests ($M_{m,w}$) in relation to the reference day for either driving, walking or transit. We conduct separate regressions with each of the transport types as the dependent variable using the same model. The independent variable is the risk perception for the pandemic ($R_{m,w}$, Google searches). As in the model described above, we use interaction terms with phase dummies p_1 and p_2 to estimate the overall effect for the first and second phase respectively and use city fixed effects and the stringency control. In addition, we use controls for mean weekly maximum temperature ($Tmax_{m,w}$) and average weekly precipitation ($Pr_{m,w}$) in city m as well as a season dummy (D_w) to control for weather and seasonal influences on mobility behavior. Furthermore, the weekly average of new Covid-19 cases per 100,000 inhabitants is here used as a control. The overall model thus reads as

$$\begin{aligned} M_{m,w} &= \alpha_1 R_{m,w} \cdot p_1 + \alpha_2 R_{m,w} \cdot p_2 + \beta Pr_{m,w} \\ &+ \gamma Tmax_{m,w} + \zeta cases_{m,w} + \eta S_{C,w} + \theta D_w + \sigma_m + \epsilon_{m,w} \end{aligned} \tag{3}$$

Again, α_1 and α_2 are the main coefficients of interest (Fig. 4, Overall response). For analyses on the country level, the data are again split and the same model is applied to the individual country-level datasets (Fig. 4).

Some cities included in our analysis might be subject to common shocks, for example through government policies released on country- or state levels. In the country-level regressions, we hence cluster standard errors by state. The exception is the United Kingdom, where all cities are in England and errors are therefore clustered on the city-level. For the overall panel regressions, we perform robustness checks by clustering errors on the city-, state- and country-level, respectively (compare SI Appendix, Section 3, Table S4, Table S5). The city-level clustering likely underestimates the error, the country-level clustering likely overestimates it.

Estimating the relationships between Covid-19 cases, perceived risk and mobility behavior changes in two separate regressions avoids concerns regarding endogeneity as the associations between actual risk levels and behavioral response could imply causality in either direction. In the main model, we use Covid-19 cases as a control variable. However, as this variable is a potentially endogenous control term which might bias the results (Bellemare, 2015), we conduct a robustness check excluding this control which largely preserves the results (compare SI Appendix, Section 3, Fig. S6).

As an alternative to the linear model with interactions for the first and second pandemic phases, we employ binned fixed-effects panel regression models (for details see SI Appendix, Section 3.h). This approach flexibly allows for nonlinearities and hence provides a robustness check as to whether the relationships we assess are approximately linear. As an additional check, we provide scatter plots of the demeaned variables. Both checks for equation (2), analyzing the influence of new Covid-19 cases per 100,000 inhabitants on attention paid to the pandemic, show near-linear relationships for both phases for the overall panel (SI Appendix, Section 3.g, Fig. S14, S15). The robustness tests for equation (3), assessing the impact of attention paid to the pandemic on mobility, show near-linear decays of mobility with rising attention in the first pandemic phase (SI Appendix, Section 3.g, Fig. S14, S16). In the second phase, we find some non-linearities, in particular a saturation response with higher attention levels. However, the comparisons of average effect sizes across pandemic phases are preserved using this non-linear approach. Overall, the linear modeling approach has the advantage of allowing for a precise comparison between the pandemic phases, as they are estimated within the same model which facilitates interpretation.

2.8. Indicator data and correlation analysis

We qualitatively assess a range of indicators related to demographics, mobility infrastructure, government trust and Covid-19 policy that potentially contribute to the heterogeneity in the risk responses observed between countries. National income data, measured as the pre-tax national per capita income at purchasing power parity in 2020, as well as an inequality indicator, defined as the national income share of the bottom 50%, both originate from the World Inequality Database (2021). The share of the population older than 65 years (POP > 65; Fig. 5) is provided in the World Bank Database (Worldbank, 2021). Data on the number of vehicles registered per 1000 inhabitants in 2019 (Vehicles p. 1000; Fig. 5) stem from the European Commission (2021) for the EU countries, the Federal Highway Administration for the US (FHWA, 2021) and the national Ministry for Infrastructure for Brazil (2020 data) (Ministério da Infraestrutura, 2021). The rail usage indicator is based on the million passenger-kilometers traveled by rail in 2019 and originates from the OECD (2021b). The rail usage indicator is available for all countries but Brazil. The survey-based trust in government indicator is also provided by the OECD and reports the share of people who report having confidence in the national government in 2020 (OECD, 2021c). The population density in metropolitan areas (Metrop. Density; Fig. 5) is here computed as the average population density of the core area of the key metropolitan regions for each country (inhabitants per km^2). A metropolitan area is defined as a functional urban area with a population of 250,000 or more. For more information on the data collection and methodology please refer to the respective literature (OECD, 2012; 2021a). The indicators relating specifically to Covid-19 policies (overall government response, health containment, economic support) originate from the Oxford Covid-19 Government Response Tracker (Hale et al., 2021) (compare section 2.5).

To get an indication for the relationship between each effect measured in this study (attentiveness to Covid-19, driving response, walking response, transit response) in the second pandemic phase and each of the indicators described above, we compute pairwise Pearson correlation coefficients (Kirch, 2008) which measure linear association. The Pearson correlation coefficient ranges from -1 to 1 where negative numbers indicate an inverse relationship and positive numbers a positive relationship. Coefficients close to zero suggest no linear relationship between the variables whereas coefficients close to -1 or 1 indicate a stronger linear relationship. As the sample size in our case is low (eight countries) the strength of the correlation should be interpreted with caution. When evaluating the directionality of the association it is important to consider the desired direction of the response. For example, a positive correlation between national income and driving indicates that a higher income coincides with a larger (more positive) marginal effect of risk perception for the pandemic on driving behavior, meaning that if the income is high, driving is reduced less, translating into less risk-aware behavior. To facilitate interpretation, Fig. 5 shows the effect for the social indicator if the response is more protective (i.e. high risk perception, strong reduction in driving, walking and transit). Please refer to the SI Appendix, Section 5 Fig. S20 for a figure visualizing the raw correlations.

3. Results

3.1. Decreasing risk perception over the course of the pandemic

Assessing the overall impact of weekly Covid-19 cases on the perceived pandemic risk across all included cities empirically confirms a direct positive relationship between the actual risk and the perceived pandemic risk (arrow a, Fig. 1): With rising case numbers, the perceived pandemic risk increases. The marginal effect in weekly attention paid to the pandemic, measured as the change in the percentage of Google search requests relative to the maximum search interest for Covid-19 related terms, across all cities is positive in both pandemic phases (slope of the lines, Fig. 3). However, the marginal effect is larger in the first phase. Across all cities, an additional Covid-19 case per 100,000 inhabitants leads to a 0.33 percentage point (p.p.) increase in perceived risk. For the second pandemic phase, this effect amounts to only 0.06 p. p., translating into a 82% reduction in perceived risk from the first to the second pandemic phase. To ensure comparability between both phases, we limit the case numbers of the second phase to the maximum case level that is reached in the first phase. The analysis with the full second phase is shown in the SI Appendix, Section 3.b, Fig. S5. For this analysis all trends shown in Fig. 3 are preserved but the gaps between phases are even more pronounced. The regression table for the overall response shown in Fig. 3 can be found in the SI Appendix, Section 3.a, Table S4.

This global panel represents an average response across all cities and as such does not consider country-level heterogeneity due to, for example, differences in the strength of the local Covid-19 outbreaks and their containment strategies. Furthermore, most cities in the global panel are located in the US, implying that the panel is most strongly informed by the US response. To shed light on possible heterogeneity in risk perception across countries, we conduct separate analyses at the country level (Fig. 3). For six out of eight countries, the marginal effect of Covid-19 cases on the perceived risk is stronger in the first than in the second phase. The magnitude of the effect and the differences between the first and the second phase are however heterogeneous across countries. For example, Switzerland experiences large reductions in the marginal perceived risk between the first and second phase of around 88%: During the first phase, an additional Covid-19 case per 100,000 inhabitants led to a 8.44 p.p. increase in perceived risk whereas during the second phase this increase amounts to only 1 p.p.. In contrast, the Netherlands show a smaller decrease of around 28% (5.43 p.p. in the first phase compared to 3.93 p.p. in the second phase).

Brazil and Sweden do not display a reduction in the marginal perceived risk between the first and second phase but an increase. Brazil shows negative marginal effects in the first phase (-0.65 p.p.) and positive effects in the second phase (0.13p.p.). Sweden displays an increase in perceived risk from the first to the second phase. One possible explanation could be the unusual governance responses to Covid-19 taken during the first phase of the pandemic by international comparison. The Brazilian president publicly denied the threat posed by Covid-19, pursuing a defiant rhetoric and actively working against containment strategies (Bello, 2020). Multiple scientific studies have commented on the lack of a coordinated health policy response of the Brazilian government to Covid-19, especially in the first phase after the outbreak (Ferigato et al., 2020; Lancet, 2020). Meanwhile, the Swedish Public Health Authority has adopted what was described as a “herd immunity approach” (Claeson and Hanson, 2021), imposing little to no restrictions on the public (Bjorklund and Ewing, 2020) and limiting tracing and testing. This could suggest that the governmental response had some impact on the perceived danger of the virus.

3.2. Weaker behavioral response in second pandemic phase across all mobility types

As the next step, we assess the impact of the perceived risk (approximated by attention paid to the pandemic) on mobility behavior

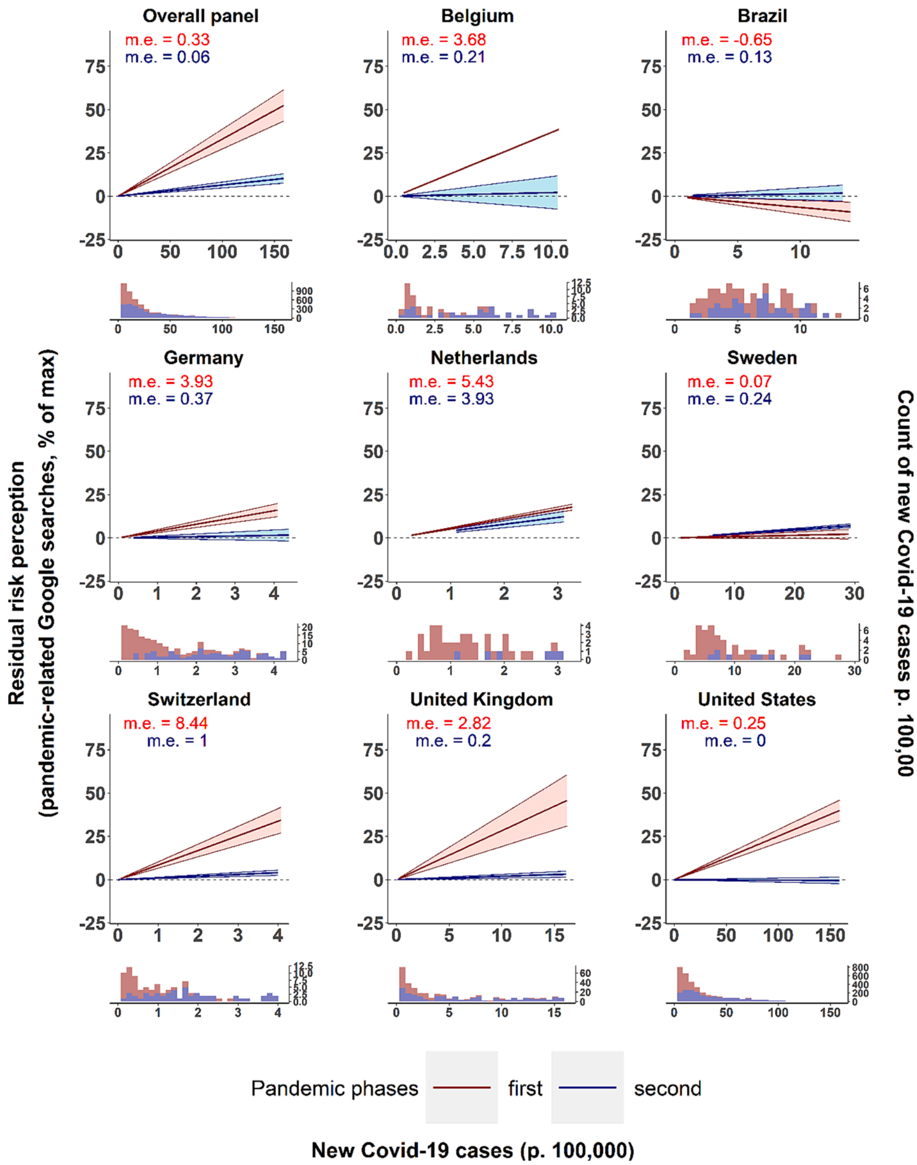

Fig. 3. Perceived risk increases with higher case numbers but this response is weaker in the second pandemic phase. *The slope of each line corresponds to point estimates of the impact of weekly Covid-19 cases per 100,000 inhabitants on risk perception for each pandemic phase after explicitly accounting for government interventions. Risk perception is approximated as attention for the pandemic, measured by Google search requests for pandemic-related terms. Weekly search requests are normalized between 0 and 100 for each city where 100 marks the day with the maximum requests. The left-hand y-axis shows the residual risk perception for isolating the effect of the Covid-19 cases. Cases are limited to the maximum case numbers of the first phase to ensure the comparability of risk levels. Marginal histograms show the count of days with a certain number of cases for the first and second phase (right-hand y-axis). Overall, the increase in risk perception is substantially larger in the first phase (red line), indicating a normalization of Covid-19 risk over time (Overall response). On the country level, this holds for all countries with a conventional Covid-19 policy response. The gap in risk perception between the first and second phase is heterogeneous across countries.* (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

for three different transport types: driving, transit and walking. The mobility data captures changes in Apple maps navigation requests with respect to a reference day (January 13th 2020), i.e. they capture the number of navigation requests as percent of the pre-pandemic baseline. Walking and driving are personal mobility modes and as such different from public transport which may be perceived as more infection-prone by individuals (Helfers et al., 2022; Kellermann et al., 2022). We assess changes in all mobility types to capture the full heterogeneity of behavioral response to perceived risk.

Applying the regression model to a panel containing all cities shows that elevated search trends lead to reductions in mobility across all transport types, corresponding to a strengthening of the behavioral response as perceived risk increases as hypothesized in Fig. 1. Comparing the mobility response across the first and second pandemic phase, we find smaller mobility reductions, i.e. a weaker effect in the second phase for the overall panel across all transport types. For driving the marginal effect decreases by around 52%. The marginal effect is measured as the change in navigation requests, which are reported as the percentage change with respect to a reference day, in response to changing risk perception. An increase in Google search interest by 1 p.p. leads to a 0.58 p.p. reduction in driving in the first phase, compared to 0.28 p.p. in the second phase. For walking we observe a similar pattern with a decrease in the marginal effect of around 48% between phases (reduction of 0.66 p.p. to a reduction of 0.34 p.p.). For transit, we observe a mobility reduction of 0.35 p.p. in the first phase (negative marginal effect) and an increase in mobility of 0.27 p.p. in the second phase (positive marginal effect). The regression table for the overall response shown in Fig. 4 can be found in the SI Appendix, Section 3, Table S5.

Analyses for the individual countries generally confirm a strong mobility reduction in the first pandemic phase in response to an increased risk perception across all transport types. The impact on the different transport types is heterogeneous with the most affected transport type varying by country. For driving, we find the strongest significant negative marginal effect size of around 0.79 p.p. in the first phase for Switzerland, followed by the Sweden (0.76 p.p.) and the United States (0.74 p.p.). The negative effect on transit is strongest in Sweden (0.7 p.p.), for walking we also observe the strongest negative effect in Switzerland (0.67 p.p.). In accordance with the panel including all cities, the mobility response across all transport types on the country level is generally much less pronounced in the second pandemic phase. This suggests that over time, the self-protective behavioral response to perceived risk levels weakened. A few exceptions to this pattern are observed, such as in Sweden, which displays a larger negative marginal

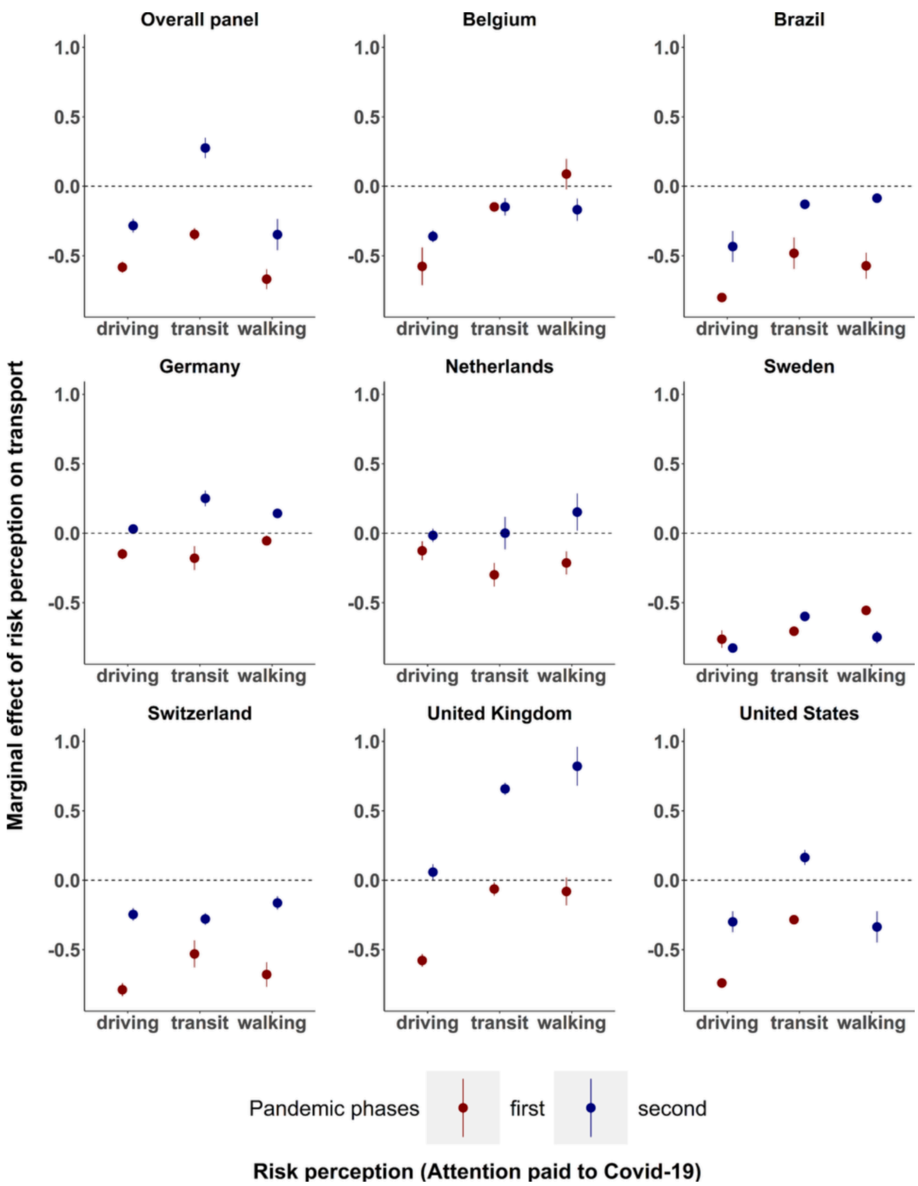

Fig. 4. Behavioral response to risk perception: Mobility is reduced but to a lesser extent in the second pandemic phase. *The point estimates show the impact of risk perception (weekly attention paid to the pandemic, measured as the percentage of Google search requests for ""Covid", "Corona", "Covid-19", "Covid19" and "Coronavirus" relative to the maximum search requests in the reference period) on the change in mobility (p.p.) for three different transport types (driving, transit, walking) and each pandemic phase. Mobility is measured in relation to a reference day in January 2020. Overall, the reduction of mobility in response to rising risk perception is substantially larger in the first phase (red points) for all transport types compared to the second phase (blue points), indicating a normalization of Covid-19 risk over time (Overall panel). On the country level, the majority of countries show a weaker response across all transport types in the second pandemic phase, providing evidence for lower self-protection efforts in response to the perceived risk over time. The transport type most affected varies by country.* (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

effect in the second phase across all transport types. As in our interpretation of Fig. 3, the unusual "herd-immunity" approach of the Swedish government to the pandemic is a likely source of this discrepancy.

Looking at the combined effect emerging from Fig. 3 and Fig. 4 (as visualized in the SI Appendix, Section 4 Fig. S19) we find evidence for a layered effect: From the first to second pandemic phase not only did the gap between actual and perceived risk widen, but the behavioral response to perceived risk also weakened. Looking at the combined effect for risk perception and the effect on the driving response, for Germany, the Netherlands, Belgium and Switzerland the overall risk response weakened predominantly through the channel of changes in attention, whereas for Brazil the United Kingdom and United States a weakening of the mobility response appeared more prominent. The combined effects for risk perception and the walking/transit responses are similar. Overall, we can interpret this as all countries but Sweden becoming less self-protective in the second pandemic phase. As large-scale vaccine distribution only started at the end of the second pandemic phase, the dominant strategy to avoid contracting Covid-19 remained one of reducing contacts and mobility throughout the time-series assessed here. The weakening of the response along both the risk perception and the behavioral response dimensions therefore provides evidence for a risk normalization process: Despite a comparable threat, the self-protection effort decreased.

3.3. Risk normalization over time – qualitative analysis of possible contributing factors

Even though there is evidence for risk normalization for the majority of countries, the extent to which the responses weaken is heterogeneous across countries and transport types. Risk perception has been shown to be influenced by a variety of social and cultural factors (Duong et al., 2021; Savadori and Lauriola, 2020; 2022), and the burden of Covid-19 has been distributed unequally across socioeconomic groups (Levy et al., 2022; Lin et al., 2021; Carrión et al., 2021). To qualitatively explore the heterogeneity in the risk responses in the context of possible contributing factors, we compute Pearson correlations between each of the marginal effects assessed in this study (effect of Covid-19 cases on risk perception, as well as risk perception on driving/walking/transit) and a range of indicators. Specifically, we consider demographic variables (national income, inequality, share of population over 65), indicators related to mobility infrastructure (metropolitan density, registered vehicles per 1000 inhabitants, rail usage), a survey-based government trust indicator and multiple Covid-19 policy indicators reporting the extent of health containment policy, the level of economic support and the overall government response.

We find that higher national income coincides with a higher risk perception response and a stronger mobility response (i.e. stronger mobility reduction) across all transport types (Fig. 5). A plausible mechanism here is that high income may – among other privileges – increase the ability to work from home and thus reduce the need to travel. This could point to economic barriers in the ability of citizens to engage in risk-mitigating behavior. The number of vehicles per 1000 inhabitants is most strongly correlated with the transit response: The reduction in transit is stronger if people have more cars available. Traveling in a car alone bears less infection risk than using public transport, this might indicate a substitution behavior among citizens with the economic means to afford private vehicle usage. Higher rail usage is correlated with a low risk perception response and low mobility responses, potentially pointing to a greater dependency on transport in countries with strong rail usage. A higher metropolitan density is also correlated with weaker mobility reductions for transit, potentially reflecting similar mechanisms.

High risk perception also correlates with an older population which could indicate an awareness for the age-specific risk burden of Covid-19. High government trust is associated with a more protective response across risk responses and all transport types. A stronger mobility response is also typically seen in countries with a weak governmental activity (government response, economic support, health containment). As we control for government interventions in the model, this could indicate that the mobility response is reduced if government guidelines are in place that people can rely on.

4. Discussion

In this study, we found evidence for risk normalization of Covid-19 over time across more than 100 cities from eight countries. Separate analyses of the relationship between the actual risk and risk perception as well as between risk perception and mobility behavior revealed a weakening behavioral response via both channels: Not only does the impact of Covid-19 cases on risk perception lessen over time but the response of mobility behavior to risk perception for three different transport types also weakens (i.e. mobility decreases less). In contrast to other survey-based studies concerned with risk behavior, we here use high resolution, high frequency data to assess the relationship between actual risk, perceived risk and behavioral response. This empirical approach allows us to analyze unprompted behavior, mapping natural reactions with little to no expectation bias. Furthermore, the high resolution of the data means that our analysis is informed by the behavior of more users than for example a survey-based set-up could capture. The high-frequency (weekly) data allow to identify dynamics across time. Specifically, we use pandemic-related Google searches to approximate the perceived risk.

Data on Covid-19 cases are subject to known measurement errors which present potential concerns for our analysis. Our methodology controls explicitly for potential sources of random errors in two ways: by removing days with negative changes in cumulative case numbers and by detecting strong outliers in their local environment (see Methods section for further details). Using these methods likely limits sources of random error in our results. However, potential systematic errors may exist which should also be considered. First, different testing capacities across locations mean that data on Covid-19 cases likely underestimate actual Covid-19 cases to different extents across regions. Nevertheless,

Fig. 5. Possible explanatory variables for heterogeneity in risk perception and mobility responses across countries. *The opaqueness of each circle indicates the strength of a Pearson correlation between the socioeconomic indicator listed in the row and the marginal response given in the column (see SI Appendix, Section 5 Fig. S21 for details). Colors indicate whether the indicator is high (purple) or low (orange) for a more protective response, with more protective meaning high risk perception and a larger reduction in driving, mobility and transit. Most notably, a more protective response coincides with higher trust in the government.* (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

our use of fixed-effects regressions, which remove time-invariant differences across regions, should account for such temporally invariant biases. Of greater concern is the possibility that testing capacity or efficacy changed over time within countries, a potential source of bias in our analysis. Most likely is that testing capacity increased between the first and second phase which could be interpreted as a source of our estimation of a weaker behavioral response to rising cases in the second pandemic phase. Nevertheless, it is worth noting that the actual number of Covid-19 cases was unknown throughout the pandemic, and the reported number of Covid-19 cases therefore constitutes the primary measure which was presented to and perceived by the public as an indicator for current risk. Given that our analysis is primarily concerned with the behavioral response to a given level of perceived risk, the number of reported Covid-19 cases is arguably therefore the correct measure to use to assess this mechanism, regardless of whether it underestimated the true number at different stages of the pandemic (Hasell et al., 2020).

Even though Google Trends provides insights into attentive behavior via one of the most globally ubiquitous search engines, search terms related to the pandemic may struggle to discriminate between search requests pertaining to the local rather than global development of the pandemic risk. It is possible that global events related to the pandemic triggered local search interest independently of local case numbers. To limit this bias, we chose to start the analysis in April 2020 as opposed to January 2020 when more than one million cases worldwide had been reached and after the observed global peak in Google searches (Fig. S18), reframing attention paid to the pandemic from an attention-worthy international news item to a crucial tool for assessing personal risk. One potential issue here is that by choosing a later start date to avoid general interest in the pandemic, we start our analysis at points during which case numbers were peaking or declining, changing the interpretation of the effects identified in the first phase. Nevertheless, additional tests demonstrate that our results are robust to changes in the start dates. Furthermore, Google Trends data are only accessible in a normalized format where search requests are scaled between zero and 100 across the sample period in each place. Having no insights into the absolute numbers of search requests, we cannot directly compare places and instead compare relative developments.

Following recent literature (Barrios and Hochberg, 2021; Ahundjanov et al., 2021; 2020) we use attention paid to the pandemic as a proxy for risk perception, in line with the rationale that the demand for information on a topic is indicative of the personal concern (Barrios and Hochberg, 2021). This measure provides a simple, globally applicable indicator of perceived risk from Covid-19 and may encapsulate perceived risks along multiple dimensions such as direct risks to physical health as well as indirect risks to personal financial stability. Distinguishing between these different aspects is beyond the scope of our analysis but offers a fruitful avenue for future work. Moreover, it is possible that changes in Google searches do not necessarily reflect changes in perceived risk but rather changes in the general need for information over the course of the pandemic (e.g. because less new and useful information is available to manage the risk). However, all new Covid-19 variants which arguably generated extensive public interest and need for protective behavior occurred in the second phase, yet we still observe a weaker information seeking behavior in the second phase. As a further possible pathway, fewer Google searches and reduced mobility behavior could also be an indicator of pandemic fatigue (Sinclair et al., 2021; Petherick et al., 2021; Harvey, 2020; Zhang et al., 2023) defined by the WHO as: "*A natural and expected reaction to sustained and unresolved adversity in people's lives which expresses itself as emerging demotivation to engage in protection behaviors and seek COVID-19 related information […]*" (Copenhagen: WHO Regional Office for Europe, 2020). Both lowered levels in risk perception and pandemic fatigue could plausibly explain our finding of the weakening behavioral mobility response over the course of the pandemic. While our method robustly identifies this phenomenon, the available data precludes a clear distinction of the specific mechanism via which the impact of Covid-19 cases on attention paid to the pandemic weakened.

The mobility data originate from Apple and report the daily percentage change of requests for directions on Apple maps. Therefore, only users that own an Apple device and choose to employ Apple maps for navigation are recorded in the data. Apple holds a large share of the operating system market (27.5% as of November 2022 (StatCounter, 2021), with slightly larger or smaller shares in some of the individual countries of our analysis (SI Appendix Section 6, Table S9). Considering the demographics of Apple customers, we can expect that our results are slightly biased towards the personal mobility behavior of younger users and those with a relatively higher income (Mobile Ecosystem Forum, 2020). Furthermore, given that the mobility data are based on routing requests, they comprise only journeys where the user employed navigation services. Of particular relevance is the fact that the available data provide only percentage changes in mobility from the levels observed on a fixed start-date. In the absence of data on the usual level of mobility, our results must rely on the fact that seasonal patterns in mobility can be properly controlled for in our regression analysis. We use continuous weather variables (temperature and precipitation) and seasonal dummies to account for such patterns, but seasonal variation may continue to influence our results. Similarly, the freedom of movement was severely impacted by non-pharmaceutical government interventions during the Covid-19 pandemic, and it is important to note that although we apply explicit controls for the stringency of government restrictions (Hale et al., 2021) at different levels in multiple robustness tests (compare SI Appendix, Section 3.e-3.g), the diversity and complexity of the national restrictions make it impossible to perfectly control for their influence.

Our study purposefully focuses on the time before Covid-19 vaccinations were widely available to the general public during which mobility reduction was the dominant strategy to avoid infection risk. Despite remaining vaccination gaps, personal risk for Covid-19 has declined substantially in the majority of countries around the world since the development and large-scale distribution of vaccines (compare SI Appendix, Section 7, Table S10). As the risk declines and societies recover, the majority of behavioral changes are likely to revert to their pre-pandemic patterns. Nevertheless, Covid-19 remains an insightful use-case for understanding how humans respond to prolonged threats. The correlations with social indicators found here, in particular those showing greater behavioral response with higher government trust and greater income, can be indicative of factors encouraging and enabling protective behavior in other crises. The World Health Organization published lists of the most urgent health threats and challenges of the coming decade (WHO, 2019; 2020). In addition to infectious diseases and structural problems in health systems, they list health impacts of climate change, noncommunicable diseases and antimicrobial resistance as the greatest health threats to humanity. The prevention and mitigation of each of these threats requires risk awareness and a personal behavioral response which implies tradeoffs between personal comfort and likely better health and safety outcomes. At the same time, all of these problems evolve on long timescales, posing a persistent threat. Understanding the mechanisms and dynamics of the behavioral response to personal risk is essential to motivate these behavioral adaptations (Ferrer and Klein, 2015; Xu and Peng, 2015). The evidence shown here for normalization of Covid-19 risk over time may forebode normalization to other threats evolving over even longer timelines and having even more subtle warning signs. For example, a slow loss of risk perception for the hazards arising from climate anomalies such as a declining remarkability of temperature anomalies (Moore et al., 2019) could have serious personal and societal consequences given e.g. the health impacts of heat stress (Kovats and Hajat, 2008). Further research is needed to understand the mechanisms leading to the risk normalization and how to best prevent it.

CRediT authorship contribution statement

A. Stechemesser: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Investigation, Visualization, Writing – original draft, Writing – review & editing. **M. Kotz:** Conceptualization, Methodology, Investigation, Validation, Data curation, Visualization, Writing – review & editing. **M. Auffhammer:** Conceptualization, Methodology, Writing – review & editing. **L. Wenz:** Conceptualization, Methodology, Investigation, Visualization, Writing – review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Data sharing statement

Daily data on mobility trends is published by Apple (https://www.apple.com/covid19/mobility). Covid-19 case data are collected from a variety of sources depending on the local reporting mechanism, the individual data sources are list in the Supplementary Information and the aggregated data set will be made publicly available. Google search data are collected using Google Trends (https://trends.google.com/trends/?geo=US). Data on Covid-19 government interventions originate from the Oxford Covid-19 Government Response Tracker (https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker). The population data are available from the simplemaps World Cities Database (https://simplemaps.com/data/world-cities) and the UN Statistics Division (https://data.un.org/Data.aspx?d=POP&f=tableCode%3A240), county level population data for the US is available from the United States Census Bureau (https://www.census.gov/data/tables/time-series/demo/popest/2010s-counties-total.html). The climate data can be downloaded from the Copernicus Climate Store (https://cds.climate.copernicus.eu/cdsapp#!/home) and from the National Centers for Environmental Information (https://www.ncei.noaa.gov/products/climate-data-records/precipitation-gpcp-daily). The demographic data can be downloaded from the World Inequality Database (https://wid.world/data/), the World Bank Database (https://data.worldbank.org/indicator/SP.POP.65UP.TO.ZS.), the European Commission (https://ec.europa.eu/eurostat/en/web/products-datasets/-/ROAD_EQS_CARHAB.), the Federal Highway Administration (USA, https://www.fhwa.dot.gov/policy-information/statistics/2019/pdf/mv1.pdf), the National Ministry for Infrastructure (Brazil, https://www.gov.br/infraestrutura/pt-br/assuntos/transito/conteudo-denatran/frota-de-veiculos-2020.) and the OECD (doi:10.1787/463da4d1-en, doi:10.1787/1de9675e-en, https://stats.oecd.org/Index.aspx?DataSetCode=CITIES#).

The aggregated data sets generated during the current study and the corresponding code will be available upon request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trip.2023.100906.

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